RISK-BASED MULTI-OBJECTIVE CROSS-ASSET BUDGET PLANNING AND ALLOCATION FRAMEWORK FOR THE INTEGRATED ASSET MANAGEMENT SYSTEM (IAMS) USING A CASE STUDY OF THE CITY OF SUGAR LAND, TX.

A Thesis

by

ALENCE POUDEL

Submitted to the Office of Graduate and Professional Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

Chair of Committee,	Ivan Damnjanovic
Committee Members,	Maria Koliou
	Sarel Lavy
Head of Department,	Robin Autenrieth

May 2021

Major Subject: Civil Engineering

ABSTRACT

A proper strategic asset management enables one to understand what network performance can be achieved, at what expense, and with what associated risks. However, the current management approaches practiced by many cities are very parochial and limited to a single asset type, justifying a need for an Integrated Asset Management System (IAMS). IAMS provides an interface on which different assets in a facility get digitally connected. It is a data-centric strategic asset management system that prioritizes the maintenance and rehabilitation schedule of various assets based on various factors like the utility, budget, condition, and so forth. This research project proposes a risk-based reliability-centric asset management approach to combine the different single asset management strategies into a cross-asset management model using a case study of the asset database at the City of Sugarland, TX. The model works on the principle that the risk associated with an asset's failure is the function of the direct and indirect cost of replacement. While the direct cost of replacement is the unit cost, the indirect cost is the additional cost related to the failure, which typically is not quantified easily in terms of the monetary units. The assets are prioritized based on the highest yearly benefit to cost ratio for replacement, with the benefit being a reduction in the expected monetary consequences of failure. The outcomes of the designed model are analyzed in terms of a reduction in the network level expected annual failure rate, an increase in the network level average reliability, and a decrease in the number of assets in a very high-risk category in the risk matrix. The end product of the research is a SQL-based quantitative tool that allows the decision-makers to prioritize the cross-asset replacement under different yearly budget scenarios, allocate the replacement budget for the assets, and visualize the results using the interface of Microsoft Power-Bi.

DEDICATION

To my father, who always used to say, "Son, if you believe in yourself and work relentlessly without hurting others' sentiments, you can achieve whatever you aim for."

I miss you, Dad!

ACKNOWLEDGEMENTS

Firstly, I would like to express my sincere gratitude to my advisor/committee chair, Dr. Ivan Damnjanovic, for giving me the opportunity to be a part of this research project and supervising me both continually and convincingly at all the time of the research. His patience, dynamism, vision, motivation, enthusiasm, and immense knowledge on the subject matter have helped me to a great extent to accomplish this task. It was a great privilege and honor to work under his guidance. Besides my advisor, I would like to thank the rest of my committee members: Dr. Maria Koliou and Dr. Sarel Lavy, for their encouragement, insightful comments, meticulous scrutiny, and scholarly advice.

Secondly, I profusely thank the staff of the City of Sugar Land, TX, for providing the data for the case study and maintaining their keen interest at every stage of this research. Their prompt inspirations, timely suggestions, and co-operation have enabled me to complete my thesis on time.

Finally, I would like to acknowledge the support and love of my family, friends, and all those closely related to me for pushing me farther than I thought I could go and believing in me.

CONTRIBUTORS AND FUNDING SOURCES

This research project was supervised by a thesis committee consisting of Professors Dr. Ivan Damnjanovic and Dr. Maria Koliou of the Department of Civil and Environmental Engineering, and Professor Dr. Sarel Lavy of the Department of Construction Science.

The material and the data used in the case study for Chapter 5 and 6 are the part of the work performed by the author as a Graduate Research Assistant (GAR) for the research project titled “Develop Risk-based Multi-objective Cross-asset Budget Planning and Allocation Framework for the City of Sugar Land Integrated Asset Management System (IAMS)”, sponsored by the City of Sugar Land, TX. The data used as the inputs for analysis were collected by using the existing single asset proprietary models provided by the City of Sugar Land, TX.

All the other works conducted for the research was completed by the author independently.

LIST OF ABBREVIATIONS

BCP	Benefit to Cost Prioritization number
COF	Consequence of Failure
COV	Coefficient of Variation
EUL	Estimated Useful Life
IAMS	Integrated Asset Management System
LOF	Likelihood of Failure
MCDM	Multi-criteria decision-making
MR&R	Maintenance, Repair, and Rehabilitation
RUL	Remaining Useful Life
SAM	Single Asset Management

TABLE OF CONTENTS

LIST OF FIGURES

Page

LIST OF TABLES

1. INTRODUCTION

1.1. Research Motivation

The network civil infrastructure systems have a direct impact on the functioning of society. All the existing civil infrastructure facilities that we see and utilize today are the result of long-term planning, resource allocation, money spent decades ago. But managing the facilities to maintain it in a usable condition is a very intricate and challenging task because it involves working with deteriorating and aging assets, budget constraints, changing customer demands, socio-economic-environmental considerations. The facilities usually include a combination of assets such as water mains, lift stations, pavements, parks, aviation, streets, IT, and so forth. These assets provide necessary services, accommodations, and foster social communication and economic development, which are the pillars for running a city. Therefore, it is vital to maintain these assets periodically.

Several organizations ranging from the government to private, are responsible for the effective maintenance of these facilities. While, at present, a vast majority of these facilities are built and managed by the government entity, there has been a significant increase in the participation of private entities over recent years. In this regard, be it a government or a private entity, these firms use different asset management models with the ultimate objective of providing a cost-effective, reliable, and resilient maintenance, repair, and rehabilitation of the facilities. If not completed on time, overall maintenance expenditure will increase significantly as more costly initiatives will be needed to reinstate these facilities to acceptable standards (Seyedolshohadaie et al., 2011).

Infrastructure facilities get exposed to increased loading and adverse weather conditions regularly, resulting in the severe risk of deterioration over time. In addition to the increase in the utility and environmental conditions, several other reasons act as a catalyst to contribute to their declining state. These include but are not limited to:

i) A lack of strategic management for planning the new and managing of existing facilities resulting in a deficiency of investment and interest in the maintenance of existing facilities.

ii) An ad-hoc over-optimistic approach to repair the structures on the verge of obsolescence resulting in a budget deficiency for the other facilities.

iii) A lack of effective asset management models to forecast the upcoming failures and prioritize the MR&R of the assets based on the benefits of maintaining the facilities to the future economy (Jamal, 2017).

Several literature reviews reveal that there has been a significant amount of work performed in the field of infrastructure management, more specifically the transportation and water infrastructures, over the decades. However, these twin mandates do not exist for other types of assets; thus, there lies a demand for an interface that can support a decision-maker prioritize different categories of assets into a unified system (Seyedolshohadaie, 2011). Furthermore, limited budgets add more problems to existing infrastructure management issues.

Industries in the United States claim to have progressed a noteworthy advancement in implementing risk management with multi-criteria analysis principles to promote their industry exercises. However, their claims remain uncorroborated because of the lack of documentation and developed applications to delineate their practices. Besides, the stakeholders would ideally want a robust module that can unionize different categories of assets into a single system and prioritize the preventive maintenance under a given budget scenario. As such, one cannot establish a module without knowledge, analysis, and execution of system reliabilities, benefits, uncertainties, and risks associated with the different assets. Thus, this research attempts to mark these concerns and connect the dots over the existing gaps.

More specifically, the following observations are the motivating factors for this research:

i. Constantly aging infrastructure facilities:

   The infrastructure facilities keep aging over time, reaching or exceeding their useful life. The decision-makers need to systematically account for the effective management of the risk and uncertainties associated with these aging facilities.

ii. Demand for a model to combine assets of different categories into a single system for decision making:

   The infrastructures in a facility usually do not have the same monitoring, failure, and maintenance conditions. At present, the available systems model these conditions only for an asset of a specific type. Thus, there lies a demand for a model that can provide a common interface for modeling different asset categories into a unified system and determine their current and future MR&R needs.

iii. Account for benefits of M&R activities.

   Typically, the representation of failure, consequence, and risk varies between assets to assets and management to management. As a result, it is extremely difficult to account for the benefits of the applied MR&R strategies in terms of the monetary units. Therefore, there lies a need for a framework that can support the decision-makers to effectively use their available resources to prioritize MR&R activities and analyze their trade-offs/benefits in monetary units.

In order to resolve the concerns discussed above, this research proposes a risk-based, multi-criteria, strategic asset management framework that supports an enterprise to monitor and manage their multi-category assets using a data-driven systematic approach. The framework accounts for the risks and uncertainties, forecasts the performance over time, prioritizes the cross-asset replacement, and evaluates the benefits of replacement in monetary units. If executed effectively, there are endless perks of this method, which range from improvement in the network level condition of the facility to an increase in their return on investment.

1.2. Research Objectives

The main aim of this research is, therefore, to access and model the risks and plan the maintenance of a wide array of assets present at any facility. More specifically, the primary objective of this research is to develop a risk-based reliability-centric model that can predict the failure of various assets, prioritize their cross-asset maintenance, allocate the maintenance funds, and mitigate the consequence associated with their failure. The end product research is focused on the development of a quantitative tool that compares the risks of one asset with another using the yearly benefit to cost ratio and prioritize the cross-asset replacement under the different budget scenario.

1.3. Our Contributions

When it comes to facility management, it involves the cumbersome task of working with a multitude of assets that may be of different kinds. It is also difficult because it requires the management to develop a common interface that provides a linkage among the assets. At present, the existing practices for most asset management firms include representing the consequences of failure and the likelihood of failure in terms of indexes or ordinal numbers. These numbers are then used to determine the risks and plan the maintenance. However, the numbers may vary according to the assets and the inspectors. As a result, the resultant risk obtained from the consequences and likelihood may be measured in the different units for the different assets.

Moreover, the indexes or numerical scorings to represent the condition of failure of the assets may not have the same definition and measure of failures within the same city. For example, the criteria of failure in pipelines may not necessarily define the failure in the pumps and vice-versa. Therefore, a risk of 5 in pipes may be completely different than that of the pumps. Furthermore, these indexes are also used to determine the benefits of the replacement of the asset. The replacement costs, however, are in terms of the monetary units, whereas the indexes are in terms of the numerical scores. This difference in the measurement units makes the approach analogous to comparing the apples with the oranges.

This paper, therefore, attempts to create that much-needed interface to make a comparative analysis between the assets by:

i. Representing the likelihood of failure in terms of the probability of failure over time.
ii. Representing the consequences of failure in terms of monetary equivalence of failure (the ordinal number for consequence times the cost of replacement).

The product of the LOF and COF now provides the expected risk, or the monetary consequences associated with the asset failure. The benefit of preventive maintenance is the avoidance of the expected monetary consequence for the following year. For example: Suppose an asset with a useful life of 10 years has the failure probability or LOF in the first year = 0.1, COF = 5, and cost of replacement = $5. Assuming that the direct cost of replacement remains constant, the benefit of preventive maintenance of asset in the 1st year is that the asset will have an expected monetary consequence of the failure of $0.25 while if done in the 10th year, the consequence will be $25. Therefore, it is now equivalent to comparing oranges with oranges.

The term preventive maintenance used in this research can be slightly misleading. Typically, in the field of infrastructure management, preventive maintenance of an asset does not add anything significant to its useful life but only decreases its current rate of deterioration. On the other hand, rehabilitation and replacement increase the useful life of the asset significantly. In this research, the terms preventive maintenance and replacement are used interchangeably because whenever the prioritized assets are considered for replacement, their replacement does not mean that the entire facility gets replaced. For example, a typical lift station facility consists of several assets such as pumps, SCADA, generators, pipes, control units, and so forth. For the SCADA panels replaced in the first year, the maintenance strategy is a replacement, but it is just preventive maintenance for the lift station facility. This example is analogous to replacing the oil filter in the car during its periodic maintenance. The maintenance strategy is again a replacement for the oil filter component but is just preventive maintenance for the car system.

1.4. Outline

This research paper consists of the following: Chapter II provides an overview of the background of infrastructure management and the management approaches practiced globally. Chapter III discusses risk and uncertainty in general, the concept of risk management, system reliability & point process, and ways to quantify risk in asset management for the decision-maker. Chapter IV presents the methodology to combine multitude of assets into a system to plan their preventive maintenance. Chapter V presents the case study where the proposed model was applied to the existing facilities at the City of Sugarland, TX. Chapter VI provides the discussion and interpretation of the results. The summary of findings, conclusions, and suggestions for future research are presented in Chapter VII.

2. INFRASTRUCTURE MANAGEMENT

2.1. Background of Infrastructure Management

As per the ASCE Infrastructure Report Card 2017, the cumulative grade for the infrastructure in the United States is 'D+', where 'A' represents the excellent condition, and 'F' represents the failure state. Total funding of $4,590 billion would be required between 2016 to 2025 to bring the infrastructures to a 'C+' or 'adequate' category. However, estimated available funding would be around $2,526 billion leading to a funding deficit of $2,064 billion, and if failed to be addressed, it would result in almost $4 trillion of GDP lost (ASCE, 2017). Thus, the poor condition of existing infrastructure, along with the lack of sufficient public investment, has produced a significant increase in rehabilitation backlogs. As a result, these backlogs induce a hurdle for the decision-makers who attempt to maintain infrastructure safe and operable. If we look at the historic data on the infrastructure grades (Table 1), we can clearly see the trend of decreasing grades from 1998 to 2017.

Table 1: ASCE Report Card Grades (adapted from ASCE, 2017)

Infrastructure	**1988**	**1998**	**2001**	**2005**	**2009**	**2017**
Aviation	B-	C-	D	D+	D	D
Bridges	-	C-	C	C	C	C+
Drinking Water	B-	D	D	D-	D-	D
Hazardous Waste	D	D-	D+	D	D	D+
Inland waterways	B-	-	D+	D-	D-	D
Roads	C+	D-	D+	D	D-	D

Table 1: Continued

Infrastructure	**1988**	**1998**	**2001**	**2005**	**2009**	**2017**
Schools	D	F	D-	D	D	D+
Solid Waste	C-	C-	C+	C+	C+	C+
Transit	C-	C-	C-	D+	D	D-
Wastewater	C	D+	D	D-	D-	D+
Overall	**C**	**D**	**D+**	**D**	**D**	**D+**

In 2000, the expenditure by the government entity (local, state, and federal) was $64.6 billion. As per the estimation by the Federal Highway Administration (FHWA), for the transportation system (pavement), in particular, there needs an increment of 17.5% in the expenditure by the government entity only to reach the projected $75.9 billion, and by 65.3% to reach $106.9 billion, to properly maintain and improve the condition levels of existing transportation assets in the United States (ASCE Infrastructure Report Card). Assuming that the essential funding is available, which is rare, the government would still require a proper asset management system to exercise its plans.

A proper asset management enables one to understand what network performance can be achieved, at what expense, and with which associated risks. The asset management systems are crucial because they assist the industrial practitioners in the assessment of the current condition, prediction of the future deterioration, selection of maintenance and repair strategies, projected condition after a repair, asset prioritization, and fund allocation (Elhakeem and Hegazy, 2012). An effective asset management system can be divided into three parts, strategic, analysis, and decision making (Cambridge Systematics et al., 2002). It is strategic because the management needs to focus on the efficiency and cost of assets to balance the priorities between the policies and objectives of the entity. It is analytic because the management needs to devise an action plan considering the historical and current data prior to making any decisions. As a result, aligning with these three principles would eventually allow the entities to accomplish their goal of effective and efficient asset management (Seyedolshohadaie, 2011).

The decision-makers are vested in optimizing the resources spent in the maintenance of the facility. For this, the decision-makers undertake the analysis at four different levels: strategic, network, project selection, and project level. The strategic level is focused on the investment analysis, fund allocations, and communicating with the funding authorities. The network-level analysis is more detailed than the strategic level and limited within an infrastructure. It answers the basic questions like what, when, where, how the infrastructure management should plan through the use of impact, need, and gap analysis. The project selection and project level are very detailed and limited to a specific project within the grand scheme of projects. This paper focuses on network-level analysis and maintenance programming for infrastructure management. At the network level analysis of a single infrastructure facility, the biggest questions that need to be answered are: a) what assets require replacement, b) when should be the replacement, and c) how much is the required expenditure? The questions get further complicated when we look at the network of infrastructure facilities, where there are assets of different kinds subjected for the replacement in the same year. Ideally, given an unlimited budget, everything would be replaced whenever needed; however, due to the limitation in the budget, the decision-maker needs to be very careful about prioritizing between the assets that need replacement and that can be backlogged. A typical infrastructure life cycle has six phases that can be divided into two stages: construction and maintenance. The construction stage begins with planning, which is followed by designing and ends with building the infrastructure. The maintenance stage, on the other hand, starts with monitoring, and is followed by rehabilitation and reconstruction. The infrastructure management focuses on the second stage of the life cycle as is often called the performance monitoring phase. It is a cyclic process where the organizations first monitor the condition of the infrastructure and then plan for the repair and rehabilitation, followed by the same procedure for the rehabilitated infrastructures. A standard asset management system, therefore, aims to provide firm grounds to monitor the infrastructure system, optimize the security, upgrades, and timely rehabilitation of facilities through cost-effective management, programming, and resource allocation decisions. In other words, it connects the engineering principles with rational management exercises and economic theories and renders the tools to promote a systematic and logical approach to decision-making. Therefore, a typical infrastructure management framework consists of 8 steps, as shown in the figure 1.

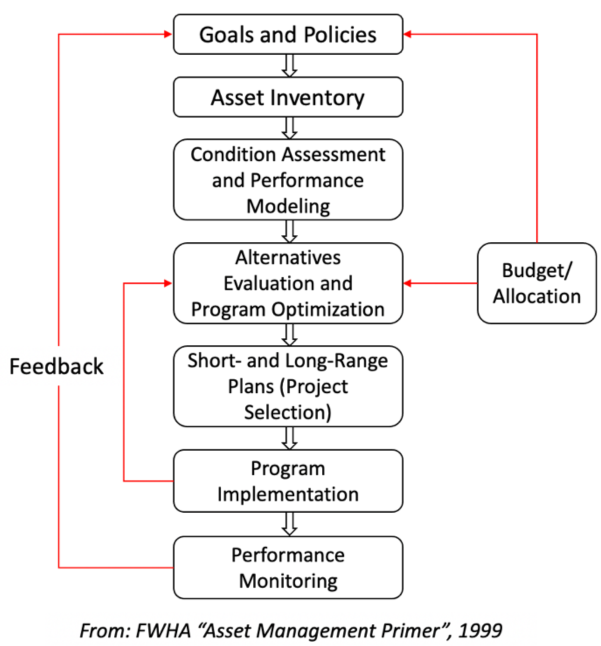


Figure 1: A typical asset/infrastructure management framework

It starts with developing goals and policies, collecting and creating the asset inventory data, quantitative condition and performance measures of the assets, economic assessment of trade-offs between alternatives, planning for selecting the options based on the available budget and investment strategies, implementing the decisions, and monitoring the performance (FWHA, 1999). As a result, an infrastructure management system connects the infrastructure database with analytical, engineering, and economic methods to make rational, objective-centric, and cost-effective decisions.

2.2. Existing Practices in Infrastructure Management

The array of infrastructure management practices in the industry is massive. While some of the organizations still prefer the conventional or ad-hoc approach, others are gradually moving towards a strategic asset management approach. The spectrum of strategic asset management includes but is not limited to the uses of system dynamics, multi-criteria decision analysis, analytical-hierarchical process, decision support system, statistical and mathematical modeling, and risk-based approaches. As a result, there has been a significant number of researches performed on the mentioned approaches over time, with the ultimate aim of developing an effective asset management approach that is reliable, versatile, efficient, and easy to use.

The conventional asset management practices usually involve a like-for-like or an ad-hoc approach. The outcome of such strategies is very parochial as a temporary focus in an issue may result in a contrary impact on other operations of other components in a system. Moreover, to keep the facilities operating at a required level of safety, serviceability, and maintainability is epoch-making, as a disruption in the service of one may have a domino effect over others. In the absence of an efficient and effective system, a failure of one asset can lead to significant economic, social, and environmental impacts on the entire network. These problems get further augmented, particularly in city areas, with increasing MR&R activities due to excessive population, utility, and aging infrastructure (Wei et al., 2020). Managing a city's infrastructure network is very strenuous as there lies a list of hurdles associated with it. The first hurdle lies in the data collection and compilation process. Here the challenge is that the decision-making process requires a variety of data ranging from installation year, utility maps, material type, thickness, diameter, construction details, local policies, and so forth, which may not necessarily be stored and organized by a single owner/entity. It will not be wrong to say that the available data usually are disintegrated, inconsistent, and in an incompatible format. As a result, it becomes cumbersome for the decision-makers to make use of it. For example: in a city council, the water mains team may use SQL for its assets database, the pavements team may use Microsoft Excel, while the IT may automate the database using some intricate programming tools. The decision-makers then have to go through the arduous task of firstly getting the relevant data and understanding it. Secondly, formatting it into a standard format and ultimately using it to plan the asset management.

The second challenge is that the assets are interdependent among one another (e.g., water mains, gas pipelines, telecommunications, power supply, and pavements). To add on, the relevant stakeholders plan and execute the MR&R of these assets individually without considering their dependencies. As a result, the maintenance of one infrastructure is likely to have an impact on the condition of other infrastructures, causing a stream of problems (Ouyang, 2014). Rehabilitation activities of the pavements can be an appropriate example for this, as it requires working on a section of the road surface, and while doing that, the water and gas pipelines, the telecommunication wires, and the power supply lines may face damage or disruption. As a result, this ignorance of the interdependencies makes it challenging for management to have a holistic view of the impacts of their actions on the other assets. The third challenge is to select a particular method/approach which could forecast the performance of the infrastructure over time, predict the consequences of a decision on the infrastructure system, and suggest the appropriate measures for it (Wei et al., 2020). The selection of an approach will again require voluminous historical data about the assets, information regarding the potential impact on the society, environment, and economy, and the possible cause and likelihood of the effects that may not be readily available. In this regard, Hadzilacos et al. (2000) applied the historic pipeline failure data in a probabilistic model to design a decision support system that enabled the managers in the rehabilitation planning and optimization for the MR&R of pipeline networks of water utilities. Fuchs-Hanusch et al. (2008) developed a model to aid the decision-making for planning the rehabilitation measures in water supply systems using historic pipeline characteristics and failure data. The problem with these approaches is that they heavily rely on historical data, which may not be available every time. On the other hand, Marlow et al. (2015), instead of relying on the historical data, used expert elicitation methods to develop a decision support tool that suggested suitable pipeline and pavement rehabilitation techniques. Ter Berg et al. (2019) proposed a methodology to access the time required for structural assets to degrade to a specific threshold condition using Cooke's model as expert elicitation. Despite avoiding the dependency on the historical data, the generalization of these methods is yet to be scrutinized for testing and prediction of consequences in infrastructure management.

Therefore, there is a need for strategic asset management that can account for the hurdles discussed above as well as aid the decision-makers to plan when, where, and what assets are needed to be maintained. However, it is difficult to accomplish this because, firstly, every asset is important in one way or the other, but the conditions governing the failure for these may differ. Secondly, there is an issue with the budget as having an unlimited budget is quite impossible (Shao and Li, 2007). In this regard, Shao and Li (2007) developed a reliability-based time centric asset management methodology to optimize the risk cost for the assets during their service life. The authors developed an algorithm to facilitate the users to determine an optimal number of maintenances for break and stratification, which gives the minimum total cost required for the asset in their entire lifespan. Nevertheless, the algorithm did not account for the various strategic policies and the dynamic relationships between them.

Strategic policies are considered one of the prominent factors that play a crucial role in long-term infrastructure performance. The decision-makers usually go through an intricate task of making a selection among all the viable options before making any conclusion. The choices include but may not be limited to budget distribution, social and environmental consequences, risk appetite, and governmental policies. Furthermore, there may be a dynamic relationship between these strategic parameters. For example, a limitation in the budget may directly influence the risk appetite of an organization, as the decision-makers might be inclined only towards eliminating the risk of those assets having a higher likelihood to fail at present. Nevertheless, if there are no constraints on the available funding, they may focus on mitigating the risk of all the assets with a high probability of failure in the next few years. In this regard, Rashedi and Hegazy (2015) developed a simulation model that allowed the decision-makers to examine the effectiveness of the different strategic decision policies. The researchers used the system dynamics approach to analyze the interactions and trade-offs among the physical condition of infrastructure, life cycle cost of maintaining it to an acceptable condition, backlogs, sustainability, and strategic policies of asset managers. The developed framework used different what-if scenarios and provided valuable outcomes for analyzing the long-term performance of an infrastructure network with the dynamics among the various attributes of asset management. Beheshti and Sægrov (2018) considered the infiltration and inflow reduction, rehabilitation rate, population growth, and energy management as the strategic parameters to analyze their interactions for an operative wastewater transport system management. Similarly, Crisp and Birtwhistle (2005) developed a methodology to combine the age and condition of the electricity transmission assets network that analyzed the effects and interaction of various MR&R scenarios on equipment failure rate, asset population, age, and state. The system-dynamics-based works show the interactions among the strategic attributes and their effects on the performance of the network; however, they lack to account for the uncertainty analysis as a factor for the decision-making.

Infrastructure management decisions should also reckon the multiple and conflicting criteria/data that are subject to various degrees and kinds of uncertainties along with engineering judgments and expert opinions. Multi-criteria decision-making (MCDM) provides an engineered methodology to integrate the different factors (monetary and non-monetary) with benefit/cost information for the stakeholder to observe and rank the alternative course of action (Kabir, 2012). The decision-making process for identifying an optimum strategy using a multi-objective decision-making process necessitates optimizing various objectives that are guided by several parameters. These parameters include construction costs, future rehabilitation costs, user costs, maintenance of traffic, quality of work, safety, impact on surrounding communities and businesses, impact on the ecosystems, and so forth (Salem et al., 2013). MDCM methods come in very handy for budget and resource allocation. It is a preferred method because when the decision-makers tend to allot funds through conducting experts' or engineers' meetings, everyone upholds and justify their projects. Furthermore, the use of the MCDM framework in asset management supports the decision-maker to i) rank the performance of alternatives against multiple criteria which are generally evaluated in different units; and ii) reflect the trade-offs among multiple differing criteria and quantify the uncertainties essential for comparison of the various options (Kiker et al., 2005). However, the MCDM method also has a few limitations such as the assumption that the criteria are not correlated, the approach is analogous to the 'black box' in the cases of complex MCDM methods (i.e., a higher number of measures), and the approach typically either exaggerating or undervaluing a certain factor when the chosen criteria are either redundant or not comprehensive (Lai et al., 2005). Similarly, during the fund allocation, the ones with the best and loudest arguments get the funds allocated to their project resulting in unfair optimization of the resources. Moreover, the use of weights or indexes in budget allocation formulas also tends to make the approach unfair and subjective (Lind et al., 1997).

Different countries such as Australia, U.K., France, and Germany use scenarios based on cost-benefit analysis for the investigation of the effects of risk and uncertainty of project investments, which arise from the data, modeling techniques, error in forecasts, and so forth. The term "uncertainty" highlights that the decision-makings are usually executed based on deficient information about project schemes that are yet to materialize (Walker, 2000). While the uncertainties associated with data or modeling techniques are trivial, the risk that arose due to social, political, and environmental issues are significant that needs to be addressed and assessed (Piyatrapoomi, 2004). The main purpose of a risk-based assessment is to undertake a risk prediction assessment to mitigate negative repercussions. Most of the literature on this topic defines the term 'risk' as comprising two elements: first, the probability of a negative event occurring during an asset's lifetime of operation; second, the implication of a negative event on the performance of an asset (Berdica, 2002). The next chapter will be discussing risk, uncertainty, and the mitigating measures developed in the field of infrastructure management.

3. RISK AND UNCERTAINTY IN INFRASTRUCTURE MANAGEMENT

3.1. What is Risk?

The term “RISK” is the most vividly used word for expressing something that has exposure to danger. Risk entails uncertainty about the effects/impacts of action concerning something that we trust, frequently centering on negative, unwanted outcomes. Knowingly or unknowingly, risks have always been an integral element of one's life. When it comes to infrastructure management, the recent 2020 gas plant explosion in Houston, pipeline blowout in the Port of Corpus Christi in 2020, the collapse of a truss bridge in Ola, Arkansas in 2019, Florida International University pedestrian bridge collapse in 2019, and so forth are some of the good examples of the risk-related breakdown of the infrastructure facilities. Therefore, various organizations have defined risk based on their standards and industry practices. BSI (2010) defined the risk as to the combination of exposure (likelihood of threat) and the impact of the threat. The Association of Project Management defined the risk as to the combination of the likelihood of occurrence and magnitude of the consequence of an event. Similarly, Risk Analysis and Management for Project (RAMP) defined the risk as to the probability of change in the occurrence of an event, leading to either positive or negative repercussions. While these organizations defined risk in terms of the likelihood or probability, ISO (2009) defined risk as the effect of uncertainty on objectives of an event that causes a positive or negative deviation from the expectation. In general, we can see that the definition of risk comprises of two components: the likelihood of an event and the repercussions from the event.

$$\text{Risk} = \text{f}(\text{Event}, \text{Consequence})$$

In other words, the first component constitutes the assessment of risk, while the second is mainly focused on its management. But if we closely look into all these definitions, the terms like uncertainty, probability, consequence, and event are frequently repeated. Therefore, it is crucial to understand these components before defining the term risk.

3.2. What is Uncertainty?

Uncertainty is a state of insufficient knowledge about an event that makes it difficult to estimate the existing condition, a future outcome, or more than one possible outcome. Uncertainties are of two types: aleatory and epistemic. Aleatory, are the ones described as the uncertainties arisen due to the variability in repeated experiments, while epistemic is due to a shortage of knowledge or only partial information of the events on the part of the observer. Epistemic uncertainty does not subsist independent of the observer, hence very subjective (Damnjanovic and Reinschmidt, 2020). While the aleatory uncertainty cannot be reduced, acquiring more information or increasing the precision of the models can reduce the epistemic uncertainty to a significant degree. Since, the aleatory uncertainty is connected to the degree of randomness of an event, it is non-deterministic. On the other hand, epistemic uncertainty, as discussed before, arises mainly due to the incapability to precisely forecast the outcome and thus involves a range of possible errors. In the field of infrastructure management, these uncertainties arise mainly due to randomness, along with these three sources: data collection, performance forecasting or modeling techniques, and the discrepancy between the predicted and observed values (Piyatrapoomi et al., 2004).

The error in data collection is more of a systematic error that is primarily related to the uncertainties associated with the existing data or historical data. These systematic errors arise from the measurement, sampling techniques, or human judgments and usually compensated using proper statistical methods, establishing uniformity in data collection practices, maintaining the database records properly.

The second type of error is the fallacies induced due to the forecasting methods or the modeling techniques that deal with the uncertainties associated with the events happening in the future. The sources related to this type of error are endless as there lie several assumptions on determining any forecasting technique. Assuming a future interest, depreciation, and inflation rate while calculating the life cycle cost of infrastructure to select the most cost-effective MR&R strategy, approximating the parameters of distribution to predict the reliability of the system (e.g., shape and scale parameter for a Weibull distribution), grouping a specific type of assets into a category to model the deterioration, and so forth are some of the examples of this type of error. While this type of error can be reduced to an extent, absolute certainty cannot be achieved no matter how advanced our techniques are because the future is unknown (Piyatrapoomi et al., 2004).

The third type of error is the residual error resulting from the discrepancy between the model projected and real observed values. The primary reason for this type of error is the impossibility of the mathematical models to replicate the perfect scenarios that will happen in the real world in the future. The use of statistical distributions to project the economic benefits from the MR&R of a pavement section can be the best example of this. No matter how hard we try, there always lies an uncertainty in the forecasted AADT, fuel prices, time valuation, and other factors that contain model errors, resulting in the discrepancy in the calculated and observed values.

3.3. Assessment of Risk and Uncertainty in Infrastructure Management

Uncertainty and risk are often interchangeably used by people; however, there is a subtle difference between the two terms. The outcome of an event is unknown in the case of risk but, the probability distribution governing the outcome is known. Uncertainty, on the other hand, has both unknowns. Therefore, risk can be characterized as objective, while uncertainty is subjective. For example, suppose on a bet, getting heads on a coin toss wins a person fifty dollars every time. Given that the coin used is fair, the decision taken by an individual to accept the bet with the knowledge that he has a half chance to win is called risk. However, if the coin is biased, then the decision is defined by uncertainty because the individual knows that s/he has a chance to win but not exactly by what probability (De Groot and Thurik, 2018).

The deterioration in the condition of the infrastructures due to factors like a higher utility, climate change, loading, weathering factors, and so forth is an ongoing process. However, knowledge about the deterioration and its impact on the lifecycle, risks, performance, and cost is still lacking completeness. As a result, the quantification of risks due to the deterioration and its effective mitigating MR&R gets very complicated (Ter Berg et al., 2019). Therefore, there has been a tremendous amount of research done on topics related to risk and uncertainty in infrastructure management over the past decades. The analyses of risk and uncertainty include the use of qualitative and quantitative methods such as i) knowledge-based or expert-based techniques; ii) sensitivity assessment; and iii) probability or mathematical based model (Piyatrapoomi et al., 2004).

Some of the works focused on quantifying the risks are using knowledge-based or expert-based techniques such as elicitation of expert opinion, case-based reasoning models, predetermining the guidelines, scenario analysis, and so forth. The knowledge-based approach, such as scenario assessment, is one of the most common methodologies used to forecast the upcoming risk and uncertainty in infrastructure projects (Walker, 2000). The decision-makers create a multitude of possible scenarios and look for the possible solutions that minimize it to the greatest extent to account for the risks and uncertainties in the future. Techniques such as calculating the benefit-cost ratios, assigning weightage, calculating the impacts of risk are generally used to score the scenarios and make a conclusion. While this method provides a clear picture of the impact of the given scenario on the existing infrastructure system, it does not provide any information on the likelihood of the event (Piyatrapoomi et al., 2004). The use of what-if scenarios used in the impact analysis to compare the outcomes of different budget scenarios for MR&R of a pavement network can be an example of scenario analysis. The decision-makers compare the indicators such as the average PCI of the network, the percentage of network-miles in good, satisfactory, and poor conditions, and the percentage area of the pavement network in different conditions for different budget scenarios. Similarly, in cases where multiple assets are linked in a network, asset managers also use techniques like eliciting experts' opinions to understand the possible risk and the relevant consequences of their strategies before making complex decisions. In this regard, Wei et al. (2020) developed a web-based decision support system for asset management by defining a set of rules to show the linkage among the assets. The model used the trigger data such as pipe leakage, consequence data such as service interruption for the assets, expert judgments to account for the uncertainty in terms of qualitative likelihood, and an inference engine to anticipate the consequences of the triggers in the assets at a specific location. The findings reveal that this knowledge-based approach to integrating multiple assets and process a multitude of data supports a complex-decision process.

Similarly, another method of accessing the risk and uncertainty in the infrastructure project is using sensitivity analysis. The asset managers use sensitivity analysis before deciding because it provides them the degree to which the inputs influence the uncertainty of outcome in the project or the condition of the network. As a result, they can invest more time in that factor to minimize the potential sources of error. The World Road Congress Committee on Economics and Finance (1983) used sensitivity analysis to investigate the interactions among input variables by creating a range of feasible values using observation data and the Delphi technique to understand uncertainties in data and forecasting error in the traffic model. The researchers found that the error in the modeling techniques contributed significantly to the uncertainty in the project compared to other sources of errors.

Likewise, some of the other works focused on probability or mathematical models are based on predefined statistical distributions to determine the failure probability for an infrastructure. The probabilistic assessment of risks is a statistical method that accounts for overall uncertainties in an infrastructure management project. A probability distribution using the statistical parameters is used to model the uncertainties of input variables. The result of the analysis is the probability distribution created using the statistical parameters. For example, suppose a Cast Iron (CI) pipe has a useful life of 15 years with a coefficient of variation of 20%. We can model the failure of the CI pipe using the concept of failure probability by assuming various statistical distributions (Normal, Weibull, etc.).

Assuming the failure follows a normal distribution,

The density function for the given CI pipe is,

$$f(\mathrm{x}) = \frac{1}{\sigma\sqrt{2\pi}} \mathrm{e}^{-\frac{1}{2}\left(\frac{\mathrm{x}-\mu}{\sigma}\right)^2}$$

where,

μ is the expected mean end life of the pipe = 20 years

σ is the standard deviation in the end life = $\mathrm{COV} \times \mu = 4$

The failure function is determined using,

$$F(t) = 1 - \int_t^\infty f(x)dx = 1 - \int_t^\infty \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$$

Assuming the failure follows a Weibull distribution,

The density function for the given CI pipe is,

$$f(t) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} e^{-\left(\frac{t}{\eta}\right)^\beta}$$

where,

'β' is the scale factor

'η' is the shape factor

The failure function is determined using,

$$F(t) = e^{-\left(\frac{t}{\eta}\right)^\beta}$$

Figure 2 below shows the forecast of the failure of the CI pipe with an analysis period of 25 years using Normal and Weibull distributions.

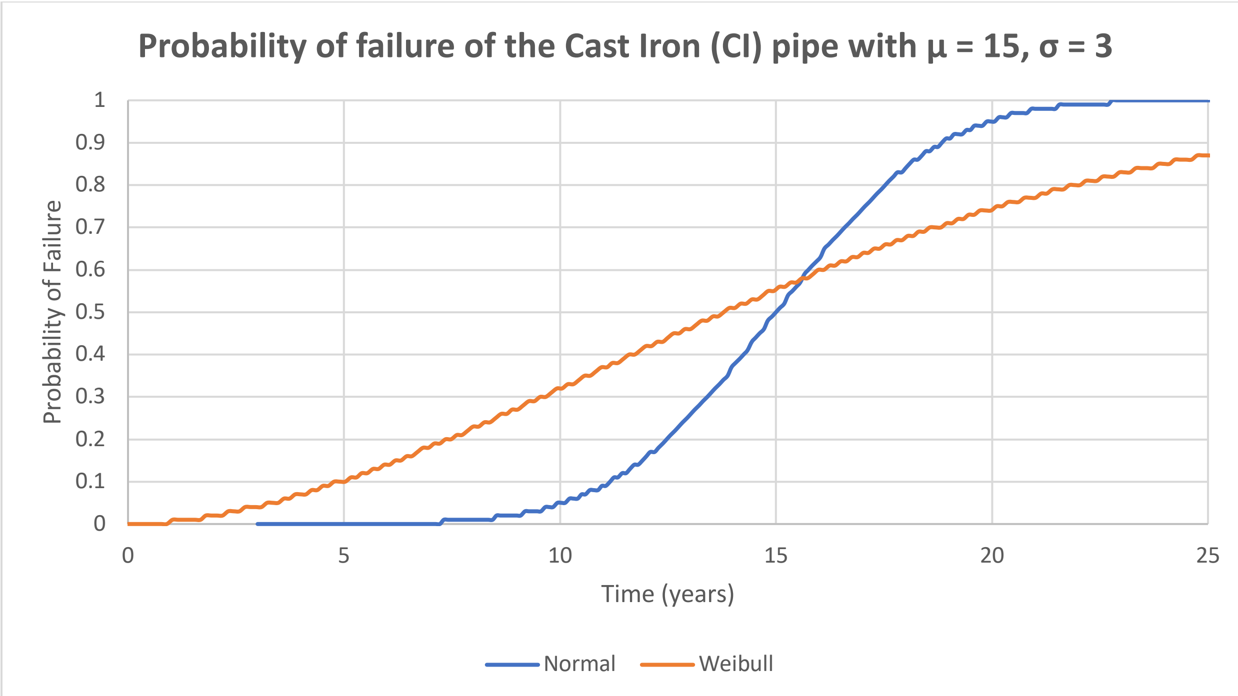


Figure 2: Probability of failure over time for the CI time over 25 years using different distributions

While both the distributions estimate the probability of failure of the CI pipe over 25 years, the Normal distribution underestimates the failure probability till the time the CI pipe reaches its assumed useful end life and then overestimates the failure. On the other hand, it is just the opposite using the Weibull distribution. The observed results, nonetheless, can be anywhere above, below, or between the two curves. Therefore, for decision-making, the use of probability distributions is a feasible tool because the uncertainties associated with the infrastructure data are quantified and modeled by a statistical distribution. In that way, it provides the decision-maker with the idea regarding the likelihood of that event to occur. However, it does not provide absolute certainty on the outcome of the event and varies among the assumed distributions. Menendez and Gharaibeh (2017) developed a methodology to account for the uncertainties associated with inputs in pavement management by modeling them in terms of probability distributions. The researchers considered the pavement condition, available budget for MR&R,

the cost of MR&R strategies, and performance predictions as the inputs. The study concluded that the uncertainties from the prediction models and MR&R costs have a significant effect on the network's performance risks. Similarly, various other probabilistic models such as Markov models (Butt et al. 1994; Mishalani and Madanat, 2002; Thompson and Johnson, 2005), survival analysis (Gharaibeh and Darter, 2003), and Bayesian models (Liu and Gharaibeh, 2014) are widely used to predict the performance transportation assets over time.

MCDM process, as discussed before, is another approach widely used by researchers for the prioritization of assets for replacement. Nordgard and Catrinu (2011) used risk criteria as qualitative measures with maintenance and cost as the quantitative measures for the MCDM in the field of the electricity distribution system for asset management. de Almeida et al. (2015) developed a multi-dimensional quantitative risk prioritization methodology based on multi-attribute utility theory. Barry et al., (2003) have developed a model that utilized the GPS and GIS data managing the roadway system for the Department of Main Roads in Western Australia. The system effectively collected and stored data for asset management, works management, and risk management. Furthermore, the system used probability-based risk assessments for MR&R and capital works using HDM-4 software. Similarly, Ype Wijnia (2011) developed an approach to draw a relationship between the risk management process and the need for asset management. However, none of them, de Alemdia, Barry, and Wijnia, considered the benefit-cost analysis for the decision-making process. On the other hand, Syed and Lawryshyn (2020) developed a risk-based decision-making framework considering risk evaluation and benefit-cost analysis for asset management. The researchers used risk tolerance criteria, benefit-cost analysis, and uncertainty reduction metrics as the parameters, along with an analytical hierarchical process matrix for the prioritization of projects at a natural gas compression facility. However, the framework did not account for the assets with unique traits.

Managing the risk for infrastructures such as water mains, lift stations, pavements on a facility, as discussed before, requires a failure model. A failure model typically predicts the lifetime of an asset that can be used to plan the M&R strategies as well as mitigate the risk. A typical failure model is developed using the concept of statistics and probability distributions. One of the earliest works on failure prediction models in pipelines was performed by Shamir and Howard (1979). The researchers developed a model that connected the number of failures in the pipe with their exponent age by dividing them into segments based on their material and diameter. Herz (1996) developed a new probability distribution using survival analysis and density function to predict the lifetime of a pipe. The researcher also divided the pipes into homogenous segments based on the pipe attributes. Black et al. (2005) used a semi-Markovian model to develop transitional matrices to evaluate the uncertainty associated with the rate of deterioration in water mains. Similarly, Kulkarni et al., (1986) used Bayesian statistics, Gustafson and Clancy (1999) used semi-Markovian analysis to model the failure of the pipeline. The researchers divided the pipe segments into homogenous sections based on the pipe attributes to model the failure pattern. However, the problem with these approaches is the assumption that the failure rate would remain the same in each homogenous group. However, this can lead to biases in the prediction (Martins et al., 2013). To overcome the biases, Jeffrey (1985) used the Cox model to estimate the Cox parameters in a water network failure data. The author linked the bathtub failure effect with the hazard function in the water network. The Cox model uses covariates to understand the influence of attributes in the failure instead of segmenting the pipe. Moreover, Le Gat (2009) used a counting process to model the failure distribution of pipelines.

The author related the rate of failure with the linear function of the number of past failure occurrences. These models are then used as a part of a risk management framework to manage, forecast, and mitigate the risks associated with the assets' failure.

3.4. Risk Management Framework

Managing the risks is one of the most important goals for any organization. For asset management firms, managing the risk by forecasting the exact period when the threshold level of service will go below the standards is extremely difficult because of two reasons. First, there are uncertainties associated with the parameters in the deterioration process of infrastructure; secondly, the lack of historical data on conditions and failures. Furthermore, the management of risks is also dependent on the risk appetite of an organization. While some own all the risks, some share it, and some delegate all to the third-party. Be it taking, sharing, or transferring, a general risk management framework consists of identifying, treating, monitoring, and managing the risks. As per the International Organization for Standardization (ISO), a risk management framework consists of assessment, treatment, monitoring, and communication of the risks. Similarly, according to the Society of Risk Analysis (SRA), a typical process of risk management comprises assessment, characterization, communication, management, and policy development. The Project Management Institute (PMI), on the other hand, considers the identification, qualitative analysis, quantitative analysis, planning for risk response, and controlling the risk in a typical risk management process. Therefore, using any risk management framework, risk can be defined as the combination of the likelihood of an occurrence of an event and its consequence (opportunity or threat) on the event; where the likelihood for an engineering project is the combination of hazard and vulnerability (Damnjanovic and Reinschmidt, 2020). Mathematically,

$$\text{Risk} = \text{Hazard} \times \text{Vulnerability} \times \text{Consequence}$$

or,

$$\text{Risk} = \text{Likelihood} \times \text{Consequence}$$

DNV (2009, 2010) recommended a risk assessment framework for the accidental events resulting in a pipeline failure. The framework analyzed risk by evaluating the frequency and consequences of accidental events. The steps for risk assessment in the recommended process include a) identification of different risks and types of failures, b) evaluation of failure probabilities, c) evaluation of failure the consequences, and d) quantification of risk for the evaluation of failure probabilities and consequences.

An asset management system equipped with an effective risk assessment technique provides a foundation for prioritizing the maintenance and rehabilitation of existing assets as well as a basis for future inspection of assets with an unknown condition (Syachrani et al., 2011). A failure to manage the risks will result in a negative repercussion to maintain the desired level of service and asset management. The repercussions include but may not be limited to the following:

i) A failure to deliver and maintain the required levels of service

ii) Damage to the reputation of the City

iii) Damage to the environment

iv) A sacrifice to the health and safety of personnel involved in managing the assets

v) Exposure to litigation

vi) A higher likelihood of backlogs resulting in exceeding budgets

Therefore, there is a need for a risk management framework that provides a more reliable identification of risks, a data-driven basis for decision-making, proactive management, efficient allocation, and utilization of resources. The framework should further improve the confidence of the stakeholders as well as be compliant with the policies. The risk management framework typically used in the infrastructure management project consists of:

i. Identification of the Risk

Typically, a risk identification process in any organization consists of a series of meetings and brainstorming sessions over time, keeping all the ideas and viewpoints in regard. A few of the common risks in any infrastructure management system are: Political Risk, Economic Risk, Social Risk, Cultural Risk, Environmental Risk, Technology Risk, and Operational Risk.

ii. Assessment of the impacts of risk

The risk assessment consists of analyzing the impacts of risks using qualitative and quantitative measures. Qualitative assessment of risk is the subjective examination of the risks by assigning a numerical scaling on the basis of their impact. The examples of qualitative measures include but are not limited to Failure Mode and Effect Analysis (FMEA), Hazard and Operability Analysis (HAZOP), Systems Theoretic Process Analysis (STPA), Fault Tree Analysis (FTA), etc.

The quantitative assessment of risks is the examination of the risks in terms of numerical risk values, such as probabilities associated with the event. Typically, it would include using simulation tools to categorize risks based on the intensities of impacts and probabilities. Quantification of risks is the process of giving a systematic consideration to the causes of each type of event and their consequences using numerical weight for making the decisions as to what to do about them. The use of numerical weightage provides significant insights, scrutiny, and consideration of the upcoming risks. The quantification of risk allows an organization to prepare contingencies for the budget, schedule, or human resources such that they could efficiently prioritize them (Duncan, 2013). There are several methods proposed by different standards to quantify the risk. These methods can be used differently depending on the nature and gravity of the influencing factors. Despite helping the decision-makers to plan and analyze the output in terms of cost, time, and resources, it is still subjective to an extent on the decision-maker as s/he assigns the probability and impacts to quantify the risks. The quantification process in all methods involves estimating the risk in terms of some numerical measures and the impact that it could mark on the outcomes. The estimation, however, can be performed using various approaches such as heuristic models, scenario analysis, probability distribution models, mathematical models, and interdependency models. After the estimation of risks, a criterion for the likelihood of all the events is defined (ISO 31000:2009). For example, suppose the probability of occurrence of an event 'A' is 0.1, then its likelihood can be assigned based on the expert elicitations or historical data for similar events, suppose 2 (on a scale of 1-10). Likewise, suppose the impact of the event 'A’ is 7 (on a scale of 1-10) estimated using a similar method. Then the risk due to event 'A' will be 14. The quantified risks are then evaluated with respect to the defined risk matrix.

A risk matrix is a matrix that is used to assess a particular risk that graphically shows the intersection of an event's likelihood and its severity against a predefined criterion. The risk matrix provides better visibility of the risks to assist the management in decision making by prioritizing the risks identified in a project, denoting the range and scores of the risks, and both qualitatively and quantitatively interpreting the risks. A risk matrix can be represented both qualitatively and quantitatively. It is represented qualitatively if the probabilities are estimated in terms of the severity of the impact (high-low) and quantitatively if both the severity and likelihood are expressed in terms of numbers. The Figure 3 below shows an example of a risk matrix (quantitative) where the red zone denotes intolerable/unacceptable risks, the orange zone as concerning risks, the yellow zone as a(n) tolerable/acceptable risk, and the green zone as neglectable risks.

			LIKELIHOOD				
			1	2	4	7	10
			VL	L	M	H	VH
CONSEQUENCE	10	VH	10	20	40	70	100
	7	H	7	14	28	49	70
	4	M	4	8	16	28	40
	2	L	2	4	8	14	20
	1	VL	1	2	4	7	10

Figure 3: A risk matrix showing the likelihood and consequences of risks

The values (1, 2, 4,7, and 10) of the likelihood signifies rare (<5% likelihood), unlikely (5-15% likelihood), moderately (15-50% likelihood), likely (50-90% likelihood), and certain events (>90% likelihood) respectively. Similarly, the values of the consequences (bottom-up) denote the severity or impact of the risks as insignificant, minor, moderate, major, and catastrophic. The insignificant impact means that the risks are easily mitigated by normal day to day process, the minor impacts result in 20% and 10% schedule and cost overrun. Likewise, the moderate impact may increase the cost and schedule by 30%, major by 50%, and catastrophic leading to the abandonment of the project (CBIS, 2016). In this project, the risk assessment is performed in terms of the failure probability and the consequences of the failure. The quantitative assessment is performed in terms of the failure probabilities, which are calculated using the system reliability and point process concepts by assuming the useful life distributions of the assets. The qualitative assessment of risks is performed in terms of the consequence of failure, which is taken from the asset inventory database, which is the maximum score of the Social, Economic, and Environmental factors which is discussed further in the next chapters.

iii. Development of the mitigation strategies

There are several risk mitigation and treatment strategies used by organizations. While developing a M&R plans the most commonly used approach, transferring the risks to the third party, establishing a contingency, changing the parameters to avoid the risks, creating an optional course of actions, and accepting the risks if no other alternatives are applicable, are some other approaches. In this project, replacing the assets with a higher yearly benefit to cost ratio is assumed to be the most-effective treatment strategy used for the mitigation of the risk.

3.5. Risk Management using System Reliability and Point Process

Reliability is the ability of a system or a component to function as anticipation under the given constraints of environment and time. It is the likelihood of success at a time 't' usually denoted by 'R(t)'. Reliability in asset management is one of the essential factors for decision making because it is directly related to cost, as the more reliable a system is, the more cost-effective it becomes. Mathematically,

$$R(t) = Pr(t > T) = \int_{t}^{\infty} f(x)dx$$

where,

R(t) is the reliability of a system/component,

f(x) is the failure density function of the system/component

t is the time

T is the analysis period

Reliability as a value is comparatively easy to be represented in an equation, but it is impossible to estimate its true extent in practice because of its reliance on more than one outcome variable. Reliability process is used in this research to plan, maintain, determine the lifecycle cost, and forecast the failure of the assets over the years.

Component level reliability can be estimated based on the distribution the given dataset follows. The most commonly used distributions are Normal, Weibull, Log-Normal, Exponential, and Beta. For a two-parameter Weibull distribution,

$$R(t) = 1 - e^{-\left(\frac{t}{\eta}\right)^{\beta}}$$

$$f(t) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} e^{-\left(\frac{t}{\eta}\right)^{\beta}}$$

where,

‘β’ is the shape factor

‘η’ is the scale factor

‘R(t)’ is the component level reliability

‘f(t)’ failure density function of a component over time.

System-level reliability can be estimated based on the reliability-wise configuration of the components. The configurations can be as simple as a few components in series or parallel or a combination of both. The most commonly used ones are series, parallel, combined series and parallel, and k-out-of-n parallel configurations. For a series configuration, the failure of a component will result in the failure of the entire system. In contrast, the parallel configuration will continue to run until one of its components operates. The k-out-of-n configuration is a special case when there is a redundant system. It requires 'k' components to function out of the total 'n' parallel components for a successful operation. In other words, a series configuration can be termed as an n-out-of-n system, while a parallel configuration can be termed as a 1-out-of-n system.

The Point Process deals with a random collection of points falling in some space where each point represents the time or location of an event. In other words, the point process is the phenomenon of an event occurring sporadically. In the point process, the likelihood of the occurrence of similar events is triggered or related to past events. For example, a panic buying or selling of stocks in one country may lead to similar events at a different county, ultimately resulting in a market rise or crash. The stock market crash of 2008 started from the United States but gradually covered the entire globe (Chilamkurthy, 2020). If the likelihood of a similar event, is increased by a past event, then the event can be categorized as a stochastically inhibited or a self-regulating event, else categorized as a stochastically excited or a self-excited event.

Nevertheless, if the probability remains unaffected, then the events are modeled as the Poison point process.

The poison point process is also represented as the Counting Process, which is a cumulative count of the number of occurrences of an event up to a current time 't' into a system. To illustrate the counting process, if 50 market crashes had happened in 1000 days since the monitoring period, N (1000) = 50. The counting process defines a function that gives the expectation of occurrence of an event at a time 't' called conditional intensity function (λ^*(t)). Mathematically,

$$\lambda^*(t) = \lim_{\Delta t \to 0} \frac{E[N(t+h) - N(t)|H(t)]}{\Delta t}$$

where,

H(t) is the history of arrivals up to time ‘t’.

λ^*(t) is the infinitesimal rate at which events are expected to occur around time ‘t’.

N (t+h) is the Point Process dependent on the history of the occurrence of event.

The self-exciting and the self-regulating process can also be defined in terms of the conditional intensity function. If the history of arrivals H(t) causes an increase in the value of conditional intensity function, then the process is stochastically excited. Similarly, if H(t) causes a decrease in the value of λ^*(t), then the process is stochastically inhibited (Chilamkurthy, 2020). However, when working with the Poison point process, the conditional intensity function is only dependent on the information about the current time ‘t’.

The next chapters will provide a comprehensive overview of the principles, methodology, and framework of the risk-based, reliability-centric, cross-asset, multi-objective asset management. The proposed methodology will be applied to the assets at the City of Sugarland, TX, as a case study, for the practical assessment.

4. METHODOLOGY AND FRAMEWORK

In the previous chapters, the relevant works on infrastructure management, which is the required introduction to basic concepts used in this research, were presented. This chapter builds the theoretical building blocks to set hypotheses required to work on the operationalization of the proposed model. Furthermore, it also discusses the methodological framework for the proposed model.

4.1. Methodology

Assets, in general, are typically managed using either an ad-hoc approach or failure prediction models. Most of the existing failure prediction model relies on the concept of statistics and probability distributions. The models work perfectly for an asset type inside a facility, given they are managed separately with a distinguished budget. But when it comes to managing assets of different categories, a single model might not necessarily yield useful or any results. For example, the water mains typically are managed using statistical models such as the counting process, Yule's process, reliability process, and so forth. These models help to forecast the lifetime performance, condition, and prioritization of the water mains. On the other hand, condition monitoring of the pavements is usually performed using the Pavement Condition Index (PCI) approach. The decisions are made by setting threshold PCI values for the pavement sections and necessary measures to be taken if it goes below the threshold. If the asset managers were to plan the maintenance strategies, then they usually use the benefit to cost ratio approach to prioritize the sections for replacement. Similarly, the assets in a Lift Station of a facility are scored through the visual inspections of the condition. The scorings are generally backed by the expert elicitation/opinion and the previous failure data. Now, suppose a city council is to plan a maintenance strategy for the next five years, provided they have funding of a million dollar every year, it becomes burdensome for the decision-makers to select between these assets as they have a different unit of measurement. The comparison of water mains with pavements and lift stations will be like a comparison of apples with oranges and bananas. Therefore, the methodology and framework described in this chapter aims to provide a solution for the asset management problem mentioned above. This research paper aims to relate the different asset management practices using a risk-based reliability-centric asset management approach. The primary objective of using this approach is to define the failure probability of the assets, the associated consequence of the failure, and relate it to derive the indirect cost of the asset failure. The indirect costs associated with the failure assets allow the decision-maker to visualize the trade-off between the assets in monetary units. Furthermore, the paper introduces a term called yearly Benefit to Cost Prioritization (BCP) number to prioritize the assets for yearly replacement. The BCP number is the ratio of the product of the failure probability and the indirect cost of replacement of an asset with the direct cost of replacement. It helps the decision-maker to compare the benefits of replacing an asset (e.g., water mains) to replacing another asset (e.g., pumps) in the same year.

In this paper, we have divided the assets into two categories: linear assets and point assets. A linear asset is an asset whose failure function is governed by its length. The condition and characteristics of such assets can vary between the sections. The length of the linear assets directly influences the cost of replacement (both direct and indirect) and the maintenance prioritization. Assets like water mains, pavements, railway tracks, power lines, and so forth are some of the examples of linear assets. The MR&R strategies of the assets are prioritized by dynamically segmenting the network into the group of assets. The groups are divided based on common properties such as diameter, material, and age.

On the other hand, in point assets, the length of the asset does not influence the failure function and the maintenance strategy. Therefore, instead of replacing a part like the linear assets, the entire asset is replaced. For example, units of pumps in a lift station are replaced compared to replacing a section length of an AC pipe of a specific diameter. Some of the examples of point assets are pumps, SCADA panels, railway switches, and traffic cameras.

4.1.1. Methodology for Linear Assets

Linear assets have fixed coordinates (start and endpoints) and are measured in linear units. The length can be divided into small homogenous management sections for prioritizing the treatment. In this research, we have integrated two concepts of statistics used for modeling the failure across the linear assets: the point process and the reliability process. A point process is generally used to model the failure of water mains assets such as pipelines. The results from the point process work perfectly fine for the network-level analysis of a linear asset; nevertheless, it lags when accessing the component level analysis. In other words, the results provide the condition of the overall network but do not provide any information regarding the expected number of failures in individual sections. Since the primary aim of this project is to create an interface for comparing assets of different categories for prioritizing the replacement, the counting process modeling falls short under this because it is not used to model the point assets. Therefore, this paper uses the concept of reliability process to prioritize the replacement of various assets of different kinds. The reliability process uses the concept of failure probability to plan maintenance, determine the life-cycle cost, and forecast the failures.

For the Point Process, the conditional intensity or the rate of failure function is calculated as:

$$\lambda^*(t) = \lim_{\Delta t \to 0} \frac{E[N(t + \Delta t)] - E[N(t)]}{\Delta t}$$

$$\lambda^*(t) = \frac{dE(N(t))}{dt}$$

$$E(N(t)) = \int_0^t \lambda^*(t)dt = \Lambda^*(t)$$

where, $\lambda^*(t)$ is the infinitesimal rate at which events are expected to occur around time 't'.

$E(t)$ is the expectation of failure at a time 't'

$\Lambda^*(t)$ is the cumulative rate of failure.

Let us consider homogenous sections where expected number of failures follow a binomial expectation. The binomial distribution in statistics is the discrete probability distribution with two parameters: the number of independent experiments (n), and the probability of success in each (p). In the case of a single experiment (n=1), the binomial distribution is also called a Bernoulli distribution or trial. The sequence of outcomes of a Bernoulli experiment is called a Bernoulli process.

Therefore, the failure probability of a section in first year is,

$$\int_0^1 f(t)dt = F(t = 1) = P_f$$

where, F(t) or P_f is the failure probability.

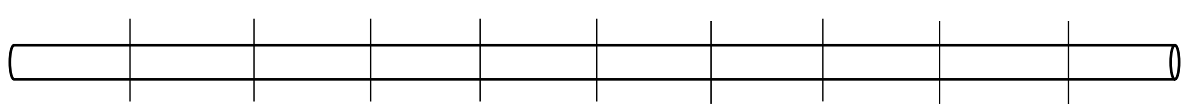


Figure 4: Segmentation of a sample 10-mile section

Consider a 10 miles pipe homogenous section with 10 segments each 1 mile long as shown in the figure above. Here,

Length (L) = 10 miles and number of segments (n) = 10

Assuming segments are independent, the probability of failure using reliability process in each segment is determined by:

$$F(t) = \int_0^t f(t)dt$$

i.e., for each segment in year 1, $F(t = 1) = \int_0^1 f(t)dt$ (i)

Expected number of failures in n =10 trails,

i.e., $E(n = 10) = n.F(t)$ (ii)

From Point Process,

$E(\text{Total Failure in 10 miles section}) = 1 = \int_0^1 \lambda^*(t)dt$ (iii)

Combining (i), (ii), and (iii),

$$n\int_0^1 f(t)dt = \int_0^1 \lambda^*(t)dt$$

$$\text{i.e., } f(t) = \frac{\lambda^*(t)}{n}$$

Therefore, the failure density of a section is the ratio of rate of failure by the total number of sections. Similarly, the probability of failure 'F(t)' of the sections can be determined from the rate of failure function.

$$\text{i.e.,} F(t) = \int_0^t \frac{\lambda^*(t)}{n} dt$$

4.1.2. Methodology for Point Assets

Unlike the linear assets, point assets are the size and location-specific assets. They do not require segmentation for the treatment prioritization. Nevertheless, they are categorized into groups of similar kind and size for studying the failure pattern and prioritizing the treatments. Equipment, machines, fleets are some of the examples of point assets. The modeling of point assets is easier compared to the linear assets because the condition function is entirely dependent only on the type of asset. For example, all the submersible pumps are designed in such a way by the manufacturers that they have a particular pattern of failure over time. This will make it easy for the managers to model the submersible pump, predict the condition from the available data, and prioritize the treatments. Similar is the case with the bypass pumps, valves, SCADA panels, generators, and so forth.

At times, the current age of an asset maybe two years, however, it may show the failure characteristics of the assets that are ten years old or more. Modeling the condition considering the current age in this scenario would result in the failure of the asset before the projected time leading to several consequences. To resolve that, these assets should be modeled considering their behavioral age as the real age. Therefore, in this project, the available condition function of the point assets is used to calculate their effective or behavioral age. The effective age is assumed to be a function of the Estimated mean Useful Life (EUL) and the Coefficient of Variation (CoV). For example, if a SCADA panel installed two years ago shows the failure characteristics of the SCADA panels that are ten years old, the effective age of the panel should be considered as ten years to forecast its performance over time.

Assuming the failure pattern is represented best by the Weibull distribution, the values of EUL and CoV are then used to estimate the shape (β) and scale (η) parameters of a 2-parameter-Weibull Distribution. The reasons for using a Weibull over a Normal distribution are that firstly, a lack of adequate data (which is very common in asset management) can make a normal distribution completely scattered. Secondly, solutions in the Normal distribution ranges from $-\infty$ to $+\infty$, whereas the Weibull distribution has closed formed solutions. Additionally, in the network level analysis of infrastructure systems, asset managers gradually keep on fixing the problems with the assets resulting in the shifting of the Normal distribution to the upper side. Moreover, Weibull distribution is very versatile as it takes the shape of different types of distributions based on the value of its shape parameter. Therefore, assuming that the point assets, irrespective of their sizes, follow the Weibull distribution, the failure pattern in the assets is estimated using a Weibull Conditional Reliability Function.

The Probability density function is estimated using:

$$f(t) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} e^{-\left(\frac{t}{\eta}\right)^{\beta}}$$

The Failure Probability Function is estimated using:

$$F(t) = 1 - e^{-\left(\frac{t}{\eta}\right)^{\beta}}$$

The Reliability Function is estimated using:

$$R(t) = e^{-\left(\frac{t}{\eta}\right)^{\beta}}$$

The Conditional Survival Reliability Function is estimated using:

$$R(t|T) = e^{-\left(\frac{T+t}{\eta}\right)^{\beta}-\left(\frac{T}{\eta}\right)^{\beta}}$$

where, β and η are the scale and shape parameters of a 2-parameter-Weibull Distribution

The shape and scale parameters can be estimated from the Variance (Var(X)) and the Mean (E(X)) functions using:

$$\mathrm{Var}(X) = \eta^2\left[\Gamma\left(1+\frac{2}{\beta}\right) - \left(\Gamma\left(1+\frac{1}{\beta}\right)\right)^2\right]$$

$$E(X) = \eta\Gamma\left(1+\frac{1}{\beta}\right)$$

While some assets fail before the expected life, many go past the expected life. Therefore, we have used survival analysis to estimate the reliability of the assets that have survived a certain period. For example, assuming a pump has an effective age of 10 years, estimated useful life of 10 years, and variance 4. We can predict the pump's reliability over time to check what would be the optimal replacement time for the pump. However, given that pump has already survived 10 years, the reliability projection should be based on considering its survival. In this case, the use

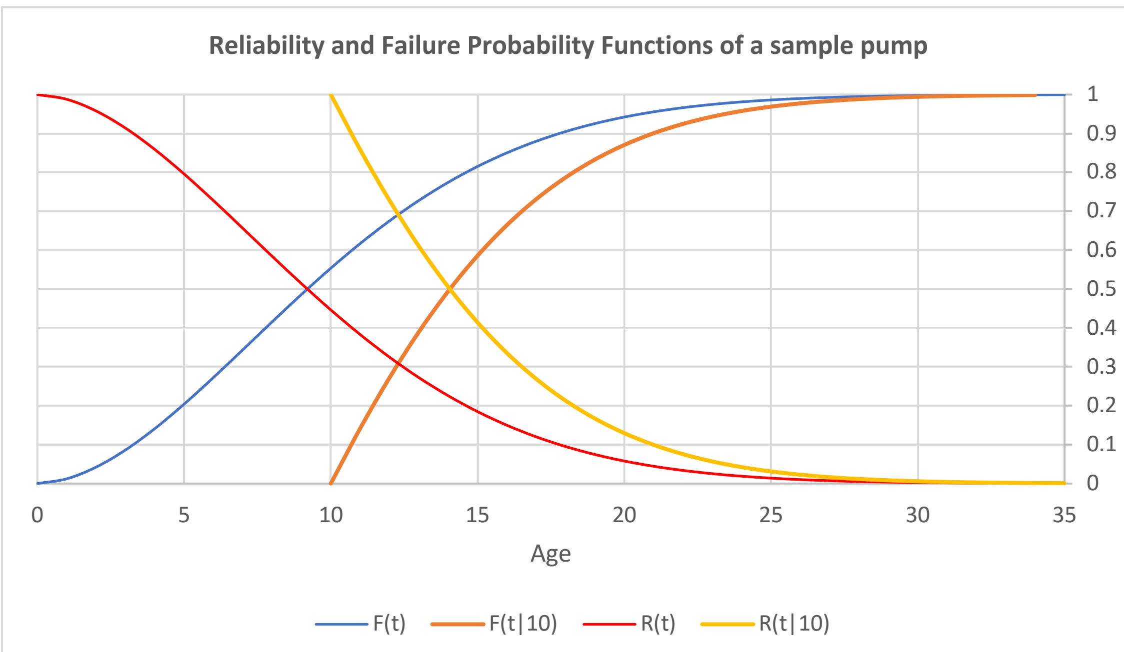


Figure 5: Conditional Reliability and Failure Probability of the sample pump that has survived 10 years.

of conditional survival reliability function is used to project the failure of the pump that has already gone past 10 years of its life yet has not failed. Figure 5 above shows the reliability R(t) and failure probability F(t) function of the pump above motioned in the example.

In the figure, we can see that the for a new pump, the reliability and the failure probability in the 10^{th} year will be 0.45 and 0.55, respectively. Given that the pump did not fail, if the decision-maker fails to account for the survival before the next modeling, s/he would be significantly underestimating the reliability and overestimating the failure probability of the pump.

Accounting for the survival, on the other hand, would show that the reliability and the failure probability in next year 10 years will be 0.129 and 0.871, respectively, which are significantly different than the first values.

The same thing can also be explained using the probability density function for the pump. The figure below shows the probability density function of the sample pump, where the blue line 'f(t)' represents the density function at present. The orange line 'f(t|10)' shows the density function given that the pump has survived the first 10 years. Since the area under the density function should be equal to one, we can see that the area under both curves is 1.

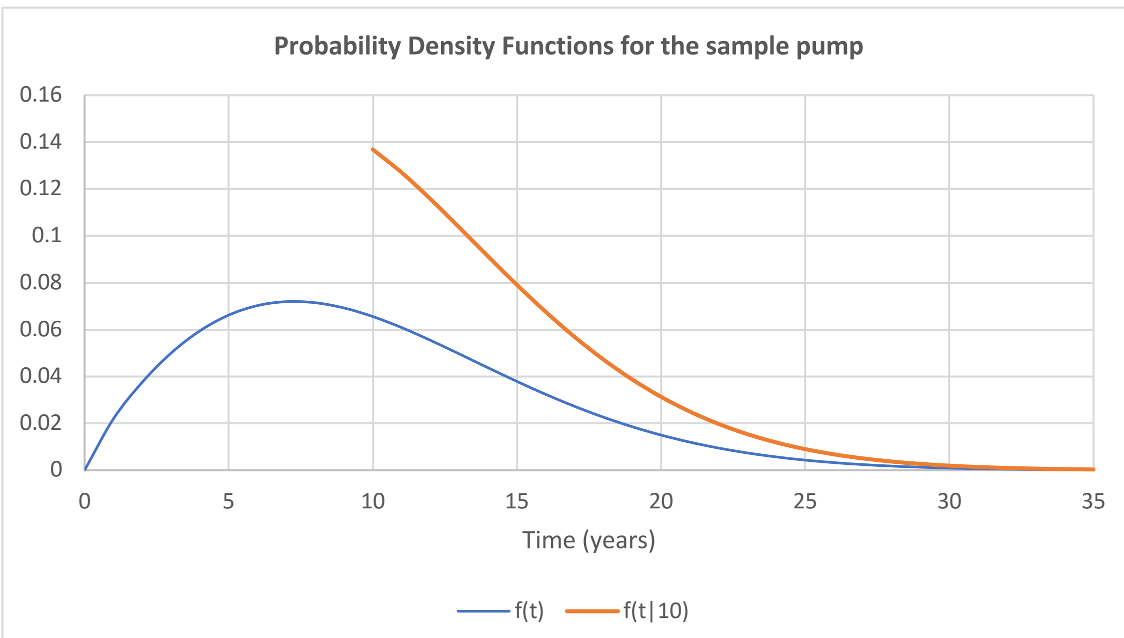


Figure 6: Probability density function of the sample pump that has survived 10 years.

4.1.3. Methodology for Cross-Asset Prioritization

The problem with the existing models used in asset management is that they do not provide any comparison between the linear and point assets. While these models perfectly prioritize the single-assets sections for maintenance, the output from the single asset models does not provide any reference for multi-asset prioritization. In the proposed IAMS model, the results from both the linear assets and points are calculated in terms of failure probability, thus, referring to cross-asset maintenance prioritization. However, the probabilities are not directly used to ranks the linear and point assets together because there is another factor- the COF associated with asset's failure- which needs equal importance. COF, however, cannot be used alone because they are represented in term of the ordinal numbers and does neither account for the probability failure nor the monetary consequences. Therefore, we use a yearly Benefit to Cost Prioritization (BCP) number to delve into the benefits of replacing particular assets compared to others in a specific year in terms of monetary units. The BCP number is a function of the expected monetary consequence associated with the asset's failure Mathematically,

$$\mathrm{BCP} = \mathrm{f}(\mathrm{F}(\mathrm{t}), \mathrm{COF}, \mathrm{Cost})$$

where,

F(t) is the probability of failure over time 't'.

Cost is the direct cost of replacement of the asset.

COF is the consequence associated with the failure which can be mapped as the indirect cost as shown in the table below.

Table 2: Mapping the COF into Indirect Cost

Direct Cost	**COF**	**Multiplier Factor**			
		0.5	**1**	**1.5**	**2**
		Monetary Equivalence			
$5,000.00	**1**	$2,500.00	$5,000.00	$7,500.00	$10,000.00
	2	$5,000.00	$10,000.00	$15,000.00	$20,000.00
	3	$7,500.00	$15,000.00	$22,500.00	$30,000.00
	4	$10,000.00	$20,000.00	$30,000.00	$40,000.00
	5	$12,500.00	$25,000.00	$37,500.00	$50,000.00

Direct Consequence = Direct Cost of Replacement (RC)

Indirect Consequence = Service Interruption Cost (SIC)

$$\text{Total Consequence of Failure (\$)} = \text{RC+SIC}$$

Then,

$$\text{Expected Monetary Consequence} = F(t) \times \text{Cost of replacement per unit} \times M$$

where, M is the multiplier factor used for the COF

$$\therefore \text{BCP} = \frac{\text{Expected Monetary Consequence}}{\text{Direct Cost of Replacement}}$$

Since all the assets inside a facility will have the following:

i. the consequence associated with its failure
ii. the probability of failure over time, and
iii. the cost of replacement

The use of the BCP number in prioritizations provides us the information regarding the benefit (avoidance in paying the expected monetary consequences) if the asset is replaced this year then the following years. It also provides a common interface to relate the linear assets with the point asset. Furthermore, the risk trade-off between the assets can also be expressed in terms of dollars.

At this point, a comparison of the reliabilities or failure probabilities of the assets with the threshold values is beyond the scope of this research. This is because, firstly, it is extremely difficult to define the comparison indexes as the threshold values of reliabilities would require a meticulous 'calibration' procedure. The threshold values are usually determined based on the calculated reliabilities of the new or well-performing existing assets (Melchers, 1999). Secondly, the values of threshold reliabilities may differ from asset to asset or organization to organization as these values are the functions of material type, utility, probability models, mode of failure, and remaining useful life.

4.1.4. Clustering the sections for developing yearly projects

Clustering is an approach of segregating the groups with similar data characteristics and allotting them into the same group using clustering algorithms. A clustering method is an unsupervised learning method as we do not define a set of the predictor to predict the outcome of the target variables. Supervised learning has a set of predefined rules that will assign the result of a variable. An example of supervised learning is the fixed requirement to score at least 90 in a class to get a grade 'A'. The logic is pretty simple that if a student scores above 90, then s/he will get 'A'. Moreover, the grading requirement is valid across all the classes. On the other hand, dividing the students into five groups based on their height is an example of unsupervised learning. Here, the groups will be divided based on the heights of students in a particular class as there is no fixed set of rules to divide the groups. The mean height of each group can be different from class to class.

Generally, in infrastructure management, the sections identified for replacement are determined based on their yearly benefit to cost ratio. However, the retrieved sections may not be necessarily located in the same area in a specific year. Economically it does not make sense to work in the same location every other year. What makes sense is to group the sections based on their similar traits into different maintenance projects and work on them. Therefore, in this project, we have used two types of clustering approaches to group the sections into yearly maintenance projects. The two types of clustering approaches are asset-based clustering and location-based clustering approach.

i) Asset-based Cluster

The asset-based clustering approach groups the common asset type into one cluster. This approach does not require any mathematical formula to form a cluster. For example, suppose a three-year maintenance plan has identified four AC pipes, three PVC pipes, and six pumps to be replaced in random order. The asset-based clustering segregates all the ACs, PVCs, and pumps into three different groups. Then assets in a particular group will be replaced in the first year, followed by other groups. The replacement year of the group will be determined based on the average BCP number of all the assets in that group to ensure the maximization of the benefit or the minimization of the expected consequences. The primary reason for doing an asset-based clustering is to provide flexibility to the managers to find a contractor who provides the best offer for the maintenance of a particular group and replace/maintain it.

ii) Location-based Cluster

A location-based clustering segregates the spatial data of the assets into groups in such a way that the assets in the vicinity lie in the same group. A location-based clustering can be performed using any of these four types of clustering algorithms: partitioning method, hierarchical method, density-based method, and grid-based method (Han et al., 2001). In a partitioning method, the (N) number of data is divided into user-specified k-parts, where each part represents a cluster. In hierarchical clustering, each data set initially has its cluster, which is merged with others moving along the hierarchy. For example, the files and folders are stored on our local drive. While the density-based clustering groups the dataset based on the distribution and concentration of the data, the grid-based clustering algorithm divides the dataset into a grid-like structure with cells to form the cluster around the cells. In this project, we use a partitioning method called K-means for segregating the sections into clusters based on their geographic coordinates.

K-means clustering is a centroid based approach to partition the dataset, where k is the number of user-specified centroids or the division, and means is the averaging method to determine the location of the centroid. In K-means method:

- The clusters are calculated as the sum of squared distances Euclidean distances between items and the corresponding centroid:

$$W(C_k) = \sum_{x_i \in C_k} (x_i - \mu_k)^2$$

where, x_i is a data point belonging to the Cluster C_k

μ_k is the mean value of the point assigned to the cluster C_k

- Each observation x_i is assigned to a given cluster such that the sum of squares distance of the observation to their assigned cluster centers μ_k is minimized.

4.2. Framework for the proposed methodology

The figure below shows the framework of the risk-based multi-objective cross-asset budget allocation framework for holistic asset management. In the research, considering the concept of FWHA's pavement management framework, we have divided the process of holistic asset management into five groups: data collection, modeling, analysis, construction, and monitoring.

i) Data Collection: Data collection in the framework is the process of integrating the asset data into a relational database. The data includes information regarding inventory, location, usage, condition, construction, work history, and design.

ii) Modeling: The modeling process deals with using the discussed methodology for the linear and point assets to calculate and forecast their reliability or failure probability over time. The modeling process begins with using the condition function for the assets in the database (developing if unavailable) to project the condition over time. The condition function allows a decision-maker to evaluate the EUL and RUL of an asset. The condition function linked with the failure functions as discussed in the methodology examines the probability of failure of an asset over time.

iii) Analysis: The analysis process mainly focuses on developing a common interface for comparing assets for replacement prioritization. The interface here is in terms of the BCP number. The sections then get prioritized for maintenance based on the available budget and the performance goals. The budget and the performance goals specified during the modeling process can be changed as per the availability and needs.

iv) Construction: The construction process involves the development of yearly projects and implementing them to monitor the outcomes. The projects are developed by clustering the sections identified for the maintenance based on their spatial location or asset type.

v) Monitoring: In the monitoring process, the city council or the asset managers compare the results of using the integrated asset management models with their performance goals and provide feedback. In the worst case, if the actual performance does not meet the threshold standards, the two possible solutions are either to increase the funding or to lower the threshold, or both. In general, the monitoring process involves accessing:

    i. An increment in component level average reliability (Point Assets)
    ii. A decrement in network level number of failures (Linear Assets)
    iii. A decrement in number of assets in Very High- and High-Risk Category in the risk matrix. (Linear and Point Assets)

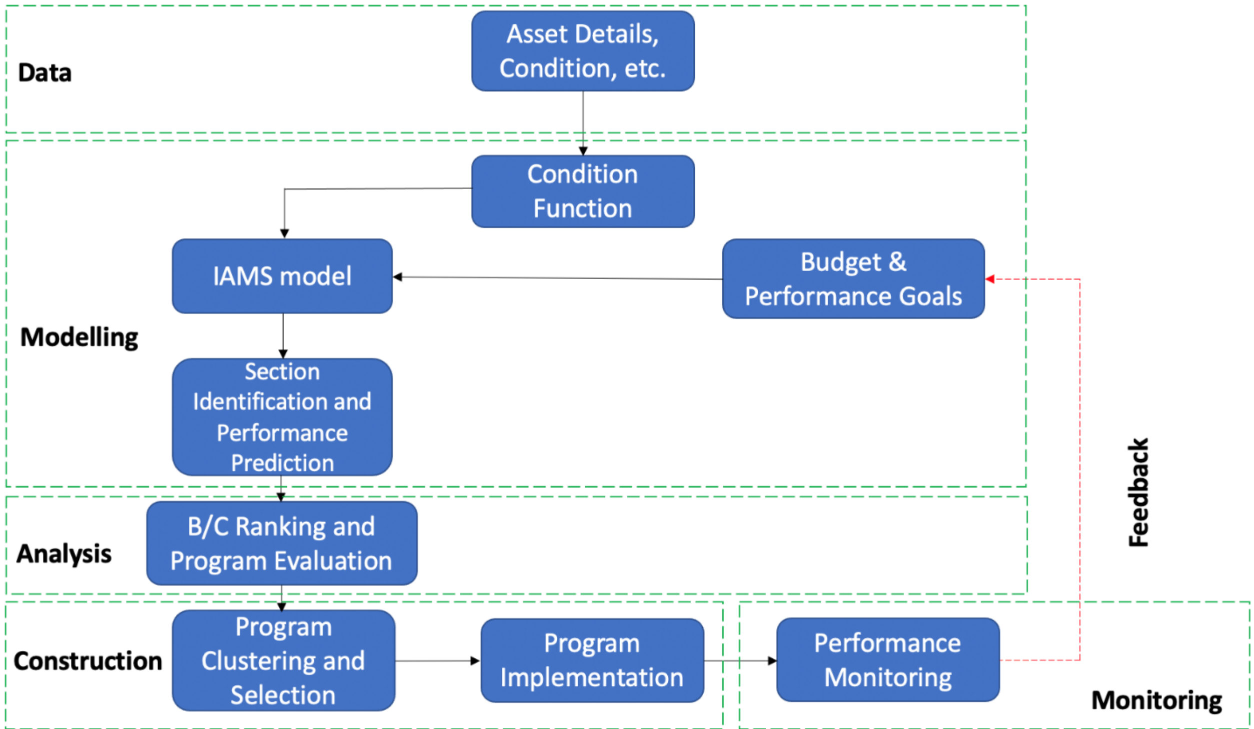


Figure 7: Framework of the proposed risk-based multi-criteria cross-asset budget allocation model

The above-described risk-based multi-criteria cross-asset framework is applied to the existing asset database at the City of Sugarland, TX. The case study along with the results are discussed in the next chapter.

4.3. System Architecture and Flow Model

The system architecture defines the arrangement, behavior, and structure of the model. The figure below shows the pictographic representation of the system architecture of the integrated asset management system model.

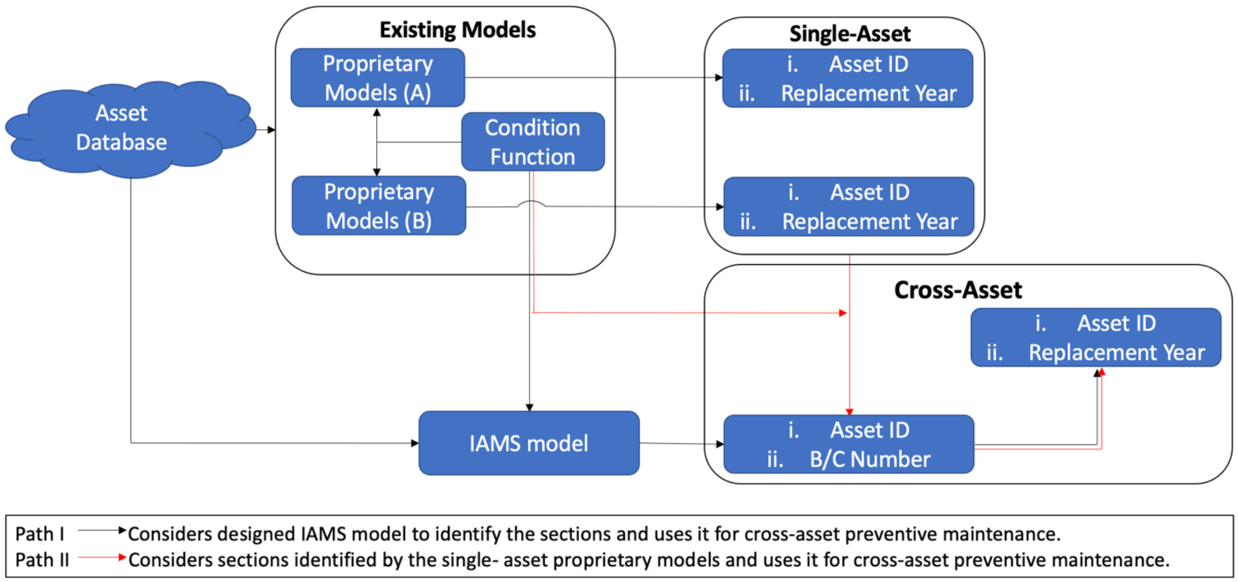


Figure 8: System Architecture for the proposed model

There are two types of input to the model, the asset inventory database or the results from the single-asset management models. In the first case, the entire asset database is considered, modeled, and the assets with higher yearly BCP number are prioritized for the replacement. In the second case, the output from the single-asset models, i.e., the list of sections to be replaced each year along with their condition function are imported into the proposed model. The model then calculates the yearly benefit to cost prioritization number for the imported sections based on whether they belong to a linear or a point asset category. The model ultimately provides the decision-maker with a list of assets (cross-assets) to be replaced every year. The next chapter discusses the model in detail using a case study, where the model was applied to the existing asset database at the City of Sugar Land, TX.

5. CASE STUDY - ASSET MANAGEMENT AT THE CITY OF SUGAR LAND, TX

5.1. Overview of the assets, their types, and their conditions

The City of Sugar Land is the largest city in Fort Bend County, TX, located 19 miles southwest of downtown Houston. Being one of the fastest-growing cities in Texas, the maintenance of existing infrastructures along with the provision for the development of new infrastructures are amongst the city's top priority. Currently, the City of Sugarland has nine different infrastructure facilities: Water, Wastewater, Mobility, Drainage & Stormwater Management, Facilities, Fleets, Parks & Recreation, Aviation, and Information Technology. As per the 2018 State of the Infrastructure Report provided by the City of Sugar Land, the overall condition of the City's assets is "good to fair". The table 3 below shows the overall condition of the assets at the City of Sugar Land, TX.

Table 3: City of Sugar Land's Overall Assets Ratings

Condition	Percentage of Total Assets
Very Good	25
Good	35
Fair	22
Poor	12
Very Poor	6

While the table above showed the overall condition of the City's infrastructure, the table 4 below show the overall condition of each infrastructure facilities at the City of Sugar Land, TX, where the letters A, B, C, D, and F represents a very good, good, fair, poor, and very poor condition, respectively.

Table 4: Overall condition of the infrastructure facilities at the City of Sugar Land

Assets \ Condition	A	B	C	D	F
Water	27%	44%	14%	8%	6%
Wastewater	17%	44%	28%	9%	2%
Mobility	36%	29%	16%	11%	9%
Drainage & Storm Water	13%	27%	43%	14%	3%
Facilities	0%	46%	39%	1%	14%
Fleet	31%	13%	32%	16%	8%
Parks & Recreation	31%	36%	27%	5%	1%
Aviation	8%	11%	30%	50%	1%
Information Technology	13%	43%	11%	6%	27%

Currently, these nine facilities are managed individually, which is creating a problem for cross-asset budget allocation and decision-making for the city council. Moreover, each of the assets within the facilities is managed using different practices of asset management. For example, the water mains are managed using a proprietary model that works on the point process to forecast the failure, whereas the lift stations are managed using another proprietary model that evaluates the failure from the visual inspections. The failure condition is the scaled to the ordinal numbers (1-5) to evaluate the risk in both water mains and lift stations. The risk is calculated as the product of likelihood (ordinal numbering of the condition) and consequence (ordinal numbers derived from the Triple Bottom Line (TBL) approach). However, there lies a problem when comparing the risks of these assets for prioritization as they are not derived using a common approach. Therefore, the developed methodology is applied to the City's asset database to manage the resources, expenditures, and priorities to achieve the threshold levels of service and benefits while maintaining the risk and life cycle costs at a minimum level.

5.2. Existing asset management practices at the City of Sugar Land, TX

The city of Sugar Land currently uses a risk-driven approach to manage the risks and prioritize the maintenance of individual asset types. The risk is calculated using a risk matrix derived from the likelihood and consequence of failure associated with the assets. The consequence of failure is calculated using a Triple Bottom Line (TBL) approach. The TBL approach considers the following factors to analyze the consequence.

i) Social Factors: The social factors deal with the impact of the asset failure associated with the consumers and stakeholders. These include:
   a. Health and Safety
   b. Operational Impacts
   c. Service
   d. Reputation
   e. Third-Party Damage

ii) Economic Factors: The economic factors deal with the threat associated cost of operation and maintenance of the assets. These include:
   a. Organizational Objectives
   b. Financial
   c. Systems, Information, and Data

iii) Environmental Factors: The environmental factors deal with the violations associated with regulatory needs such as permits, and non-regulatory needs such as degradation of environment. These include:
   a. Regulatory Compliance
   b. Non-Regulatory Compliance

The assets are visually monitored and numerically scored for each factor on a scale of (1-5) based on their severity to determine the consequence. The highest score among all the factors is considered as the COF associated with the failure of the asset. The table below shows the subjective scoring based on the level of severity.

Table 5: Numerical Scoring for the consequence of failure based on the severity

Severity	COF Score
Very Low	1
Low	2
Moderate	3
High	4
Very High	5

The likelihood of failure is determined by the condition of the asset. However, the methodology to estimate the condition varies from asset to asset. For example, the condition of water mains is evaluated using a proprietary model that relies on the principle of the counting process. On the other hand, the condition of assets in the lift stations are visually inspected based on the predetermined factors.

5.2.1. Existing asset management practice for the Water Mains

The water main at the City of Sugarland consists of a total of six types of pipes with a total length of 650 miles. The table 6 and 7 below show the overall layout of the different types of pipes in the city.

Table 6: Overview of the water mains in the City of Sugar Land

Material	Length (mi)	Description
AC	155.569242	Asbestos Concrete Pipes
PVC	481.029518	Poly Vinyl Chloride Pipes
CI	12.6345376	Cast Iron Pipes
DIP	0.63498793	Ductile Iron Pipes
STL	0.29183299	Steel Pipes
Total	**650.160654**	

Table 7: Overview of the diameter and total length of the water mains in the City of Sugar Land

Diameter (in)	Count	Length (mi)
1	39	1.31555913
2	100	1.66765439
3	59	1.16884134
4	2227	32.1747162
5	1	0.13815543
6	11745	95.7213998
8	14255	337.307816
10	159	3.2287126
12	4179	137.757171
13	2	0.00188265
14	4	0.03899858
16	466	17.7692482
18	7	0.55397109
20	165	5.71223396
24	246	9.94035702
30	49	1.21481389
36	79	4.44912225
Total	**33782**	**650.160654**

Water Mains are primarily managed using a risk-based maintenance approach. The sections with the highest risk are prioritized for a replacement earlier than the other, based on a specified budget scenario. The risks are evaluated as a function of likelihood and consequence of failure. While the consequence of failure for the pipe is evaluated using the TBL approach, the likelihood of failure is examined using the pipe characteristics and break history. The TBL approach considers the social, environmental, and economic impacts associated with the pipe failures. The risk is then calculated as the product of likelihood and consequence.

5.2.1.1. Evaluation of the Consequence of Failure

The consequence of failure is evaluated using a numerical scoring (1 to 5) based on the pipe attributes, pipe location, and customers served. The table below shows the factors, their scope, and their measurement used for evaluating the consequence in a TBL approach.

Table 8: Factors considered in Triple Bottom Line approach (Sugarland Proprietary Model)

Category	Scope	Typical Measures
Economic	Direct costs to Sugar Land for repairs or other operational costs	Pipe Diameter Pipe Service (WTP feeds)
Social	Impacts to Customers	Critical customers Type of users - zoning
	Impacts to other infrastructure	Adjacency to roads (by type), rail
Environmental	Regulatory compliance	Permit violations
	Non-Regulatory impacts	Non-regulated degradation (water bodies and environmentally sensitive lands)

The table 8 above shows an overview of the factors considered while evaluating the consequence of failure. The highest value among the factors is considered as the consequence of failure for that section. The table 9 below shows the scoring criteria for each factor.

Table 9: Scoring Criteria for evaluating the COF in Water Mains (Sugarland Proprietary Model)

Category	Criteria	Measure	1	2	3	4	5
Economic	Direct Cost to Sugarland	Diameter	<=8”	10-16”	18-24”	30”	36”
		WTP Service	NA	NA	NA	WTP Finished one valve down	WTP finished
		Depth	NA	NA	NA	>=10’	NA
		Accessibility	NA	NA	NA	Specific Aerial Crossing Identified	NA

Table 9: Continued

Social	Customer Impacts	Critical/Vulnerable Customers	NA	Public Facilities	Schools & Tourism, Large Volume Users (6 and 8” meters)	Dialysis	Hospitals & Nursing Homes
	Infrastructure Impacts	Adjacency to rail	NA	NA	NA	Within 50'	Intersect
		Roadways	Off-Road	Minor Road intersect	Major Road Within 50 feet	Major Road Intersect of Highway – within 50 ft	Highway Intersect
Environment	Non-Regulatory	Discharge to Water Body (rivers & streams)	NA	NA	Within 50’	Crossing	NA
	Levee	Flooding Potential from Levee Impact		NA	NA	Within 50 ft	Crossing

For example, 8” Water Main within 50 feet of a major road, and water body

Category Scores from the table above:

Economic COF = 1 (diameter), Social COF = 3 (roadways), Environmental COF = 3 (discharge)

Final COF = 3

5.2.1.2. Evaluation of the Likelihood of Failure

The likelihood of failure scoring is based upon the evaluation of the pipe functionality examined through the break analysis and pipe characteristics. The break analysis is conducted using the condition function from a proprietary model provided by the City of Sugar Land. The projected yearly break from the condition function is dependent on the pipe characteristics and breaks history. The table10 below shows the break equations and the parameters provided by the proprietary model for the various pipe categories at Sugar Land.

Table 10: Break equations and parameters for Water Mains

Pipe Category	Diameter	Break equation	Constant	Slope
AC	upto 12 in.	$\text{Break rate} = \text{constant} \times e^{(\text{slope} \times \text{ age})}$	8	0.0384
AC	> 12 in.		2	0.0527
PVC	upto 12 in.		2	0.0527
PVC	> 12 in.		2	0.04611
CI	all		3	0.04104
DIP	all		3	0.04104
STL	all		3	0.04104

The break rate obtained from the pipe degradation equation is evaluated against the condition score where 1 represents an excellent condition and 5 represents a failure condition. The table below shows the city's scoring for the break rate.

Table 11: Break rate to condition score conversion

Condition	**1**	**2**	**3**	**4**	**5**
Break Rate (per 100 miles per year)	<15	15 to 30	31 to 45	46 to 60	>60

In addition to the condition score, two more parameters are considered to evaluate the LOF scoring for the water mains. The two parameters are the break history and the capacity of the asset. The water mains with a history of break gets a score of 1, and others get 0. Similarly, based on the hydraulic needs data, the sections that need upsize are given one point. Therefore, the likelihood of failure is the function of condition, break history and capacity. For example, an AC pipe with a current break rate of 43 breaks/100miles/ year, no previous break history, and does not need an upgrade in size will have a LOF of 3.

5.2.2. Existing asset management practice for the Lift Stations

Lift stations fall under the group of Wastewater collection infrastructures. There is a total of 133 lift stations located at various areas in the City of Sugar Land. The lift station consists of a total of 14 different types of assets. The table below shows the overall layout of the different types of assets of lift stations in the city.

Table 12: Overview of the lift station assets in the City of Sugar Land

Asset	Count
Stationary Bypass Pump	31
Controls	133
Grounds	134
Wet Wells	134
Odor Control	4
Pipes	133
Valves	133
SCADA	133
Generator ATS	6
Submersible Pump	265
Sub Grinder Pump	17
Self-Priming Pump	2
Blower	2
Portable Bypass Pump	1

Assets in the lift stations are primarily managed using a risk-based approach. Like the water mains, the assets with the highest risk are prioritized for replacement, based on a specified budget scenario. The risks are evaluated as a function of LOF and COF. The consequence of failure for the assets is evaluated using the TBL approach similar to the water mains but with different parameters. The likelihood of failure is examined using the condition of the assets. The condition score for an asset is a function of the mortality and other failure modes. While mortality refers to the current state of operation, other failure modes refer to the current and future operational requirements of the city. The risk is then calculated as the product of likelihood and consequence.

5.2.2.1. Evaluation of the Consequence of failure

The consequence of failure is the assessment of the criticality of the asset. It answers the question of how critical the failure of the asset is to the city. The COF is evaluated considering the triple bottom line impacts of asset failure that includes social, economic, and environmental factors. The typical criteria against which these factors are scored are operation & maintenance costs, disruption in the service, health & safety of the workers, regulatory compliance, and environmental impacts. The COF evaluation considers the magnitude of impacts in each TBL category on a scale of 1 to 5, where 1 is very low, and 5 is very high. The final COF for the asset is the maximum overall score of the average of the highest score in each TBL category. The table below show the scoring criteria for evaluating the COF for the lift station assets. Suppose a SCADA panel, located within 150 feet of the commercial center, has a replacement cost of '$30000' with no staffing impact on the operation and maintenance and no environmental impacts. Then, category Scores from the table below:

Economic COF = 1 (Replacement Cost), Social COF = 3 (Health & Safety Severity),

Environmental COF = 1 (discharge)

Final COF = 3

Table 13: Scoring Criteria for evaluating the COF in Lift Station Assets (City of Sugar Land)

Criteria	Measure	1	2	3	4	5
Economic	Replace Cost	<$50,000	$50,001 - $200,000	$200,001 - $500,000	$500,001 - $1,00,000	>$1,000,001
	O&M – Staffing Impacts	No Impact	Low Impact <=2 FTE for >=1 day	Moderate Impact 2+FTE's for <+ 1 week	High Impact 2+FTE's for > 1 week	Highest (outsourced)
Social	Service Disruption Type and Magnitude	NA	Schools, Tourism & Large Volume Users	Master Pump Stations & Nursing Homes	Hospitals	NA
	Health & Safety Severity	Remote station and minor employee injury (no lost work)	Station located within 150 ft of residence or injury with lost work (<3 days)	Station located within 150 feet of commercial center	NA	NA
Environment	Discharge to Water Body - Proximity	NA	NA	Within 50' of a water body	Adjacent to a water body	NA
	Response time required before SSO	No impact	>=8 hours	2 to 8 hours	<2 hours	Immediate

The figure below shows the distribution of the consequence of failure of all the assets in the lift station.

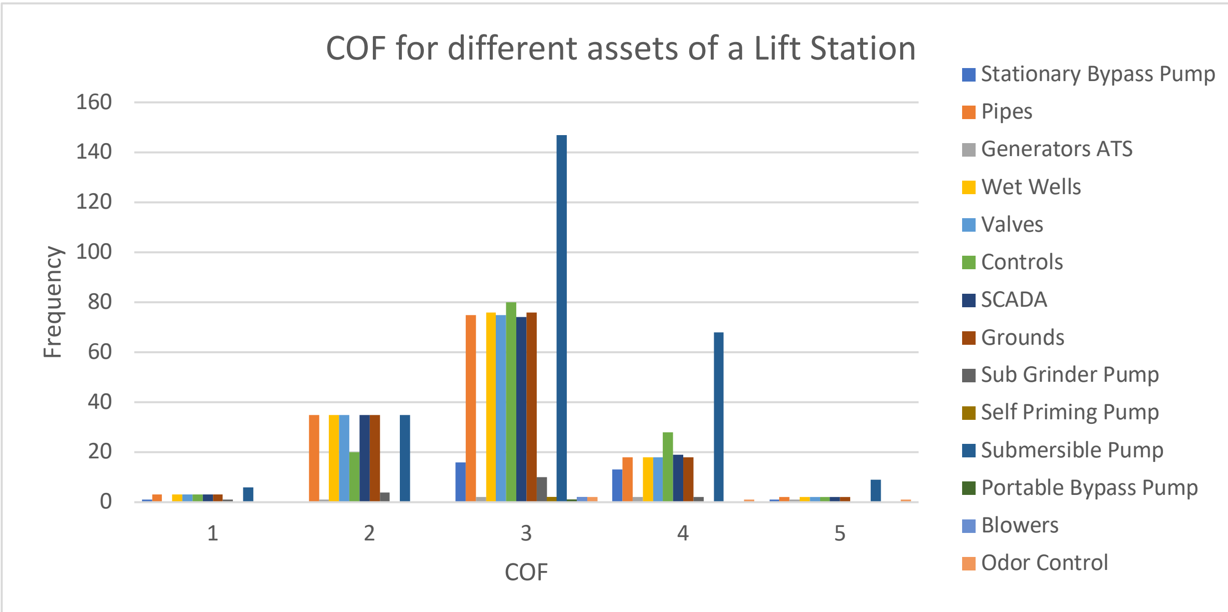


Figure 9: Distribution of the consequence of failure of all the assets in the lift stations

5.2.2.2. Evaluation of the Likelihood of failure

The likelihood of failure for the assets in the lift stations is evaluated against the different modes of failures such as mortality, capacity, level of service, and efficiency. The failure modes are divided into two categories: physical and the performance condition of the assets. These conditions are examined using asset data (such as maintenance history, operating records, previous test results), or visual inspections (by defining a set of scoring criteria), or non-destructive testing methods to estimate the condition of the assets. The table below provides an overview of the failure modes and their assessment techniques that are used in estimating the conditions of the assets.

Table 14: Condition monitoring techniques of assets in lift station at Sugar Land

Condition Type	Failure Mode	Description	Assessment Method
Physical	Mortality	Current state of repair and operation as influenced by age, historical maintenance and operating environment	Data, Visual, Test
Performance	Capacity	Does not meet demand (flow, loading, storage volume, etc.)	Data, Test
	Level of Service	Does not meet functional needs (regulatory, customer requirements, resilience)	Data
	Efficiency	Not lowest cost alternative (chemicals, power, labor, reliability, parts availability)	Data

The physical and performance condition is scored on a scale of 1 to 5, where 1 represents is an excellent condition, and 5 represents a failure condition. The tables below show the description of the scoring for the physical and performance condition.

Table 15: Physical Condition scoring and description for lift station assets (City of Sugar Land)

Score	Description
1 - Excellent	Fully operable, well maintained, and consistent with current standards. Little wear shown and no further action required.
2 – Good	Sound and well maintained but may be showing slight signs of early wear. Delivering full efficiency with little or no performance deterioration. Only minor renewal or rehabilitation may be needed in the near term.
3 - Moderate	Functionally sound and acceptable and showing normal signs of wear. May have minor failures or diminished efficiency with some performance deterioration or increase in maintenance cost. Moderate renewal or rehabilitation needed in near term.
4 - Poor	Functions but requires a high level of maintenance to remain operational. Shows abnormal wear and is likely to cause significant performance deterioration in the near term. Replacement or major rehabilitation needed in the near term.

Table 15: Continued

Score	**Description**
5 – Very Poor	Effective life exceeded and/or excessive maintenance cost incurred. A high risk of breakdown or imminent failure with serious impact on performance. No additional life expectancy with immediate replacement needed.

Table 16: Performance Condition scoring and description for lift station assets (City of Sugar Land)

Score	Description
1 - Excellent	Meets all design and legal/regulatory requirements in all demand conditions - i.e., capacity exceeds maximum designed flow and adequate standby or emergency protection provided. Overall performance excellent and meets all expected future requirements.
2 – Good	Meets all design and legal/regulatory requirements. May have minor risk under extreme conditions. Overall performance excellent and will likely meet expected future requirements.
3 - Moderate	Current performance is acceptable but would likely not meet future additional requirements or increased demand (e.g., capacity, level of service goals, regulatory requirements, reliability, obsolescence).
4 - Poor	Current performance is marginal and will not meet future additional requirements or increased demand (e.g., capacity, level of service goals, regulatory requirements, reliability, obsolescence).
5 – Very Poor	Current performance unacceptable and does not meet currently required performance criteria (e.g., capacity, level of service goals, regulatory requirements, reliability, obsolescence).

The final score of LOF is calculated as the maximum of physical or performance condition. For example, a SCADA panel has the following scores: mortality 3, obsolescence 2, reliability 3, capacity 4, operation & maintenance issues 3, and regulatory 2. From this data, the physical condition score is 3, the performance condition score is 4, and the final LOF is 4. The figure below shows the distribution of the likelihood of failure of all the assets in the lift station.

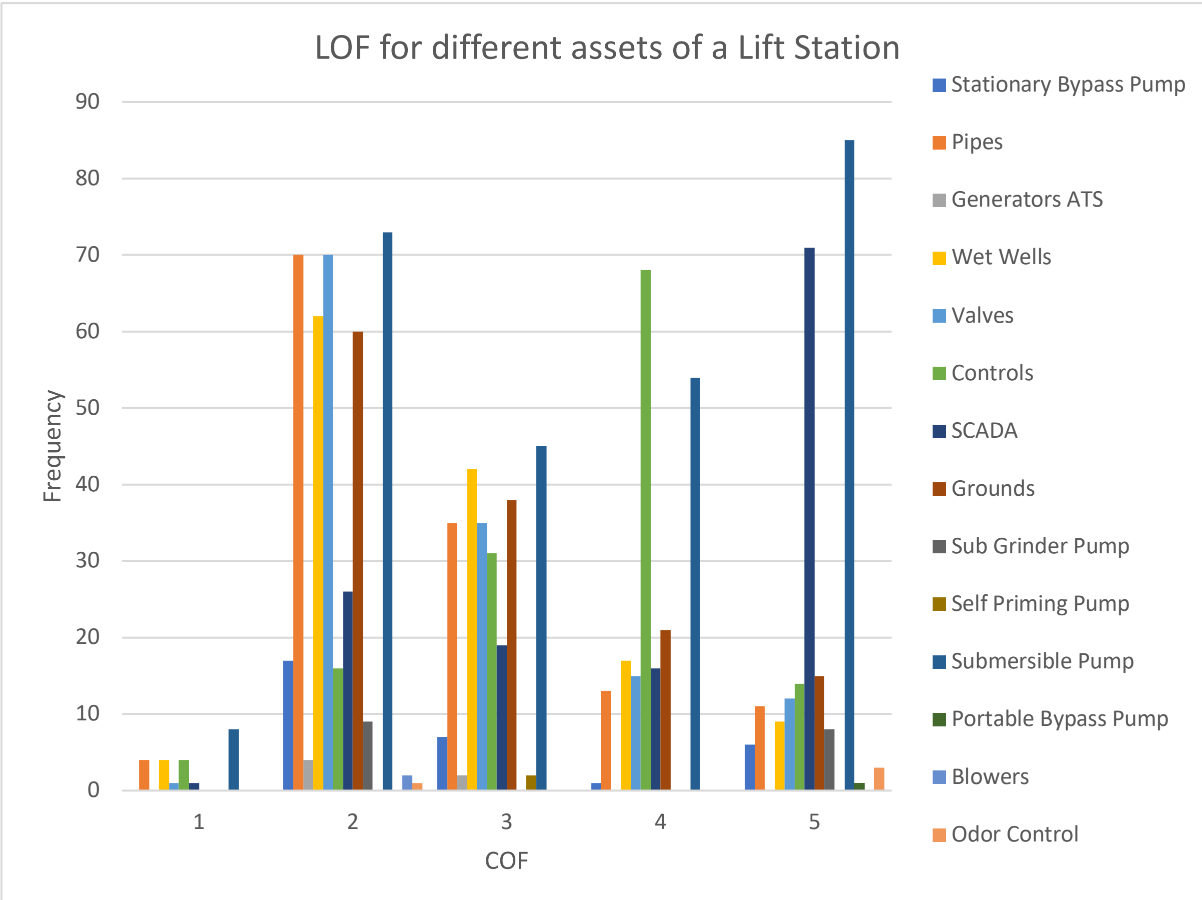


Figure 10: Distribution of the likelihood of failure of all the assets in the lift stations

5.3. Problems with the existing asset management practices at the City of Sugar Land, TX

The infrastructures in the City of Sugar Land do not have the same monitoring, failure, and maintenance conditions. The city currently uses a multitude of proprietary models provided by various consultancies for asset management. While all the models use the city's asset database to map it with the condition function to provide the list of assets for MR&R for a given budget scenario, the models are asset-specific, i.e., the model working for the Water Mains does not work for other assets. The MR&R prioritization is based on the risk-based approach, where the assets with higher risk values will be treated earlier than others. However, for integrated asset management, the values of risks between assets in different facilities are not comparable. In other words, a risk value of 10 in water mains may be more or less severe than the same value of risk in the lift stations. Furthermore, in the current models, despite using a risk-based asset management approach, the value of risk does not provide the expected monetary consequences for asset failure and the benefit of their replacement, which gives rise to the demand for an integrated asset management model. The proposed model compares risk between the assets in terms of their yearly BCP number and the benefit of their replacement in terms of the decrease in the expected monetary consequences. For example: Suppose, an asset has the failure probability or LOF in the first year = 0.1, COF = 5, and cost of replacement = $5. Then, the benefit is replacing the asset with $0.25 expected monetary consequence in the first year rather than $25 when it completely fails.

The proposed model will consider the output from asset-specific proprietary models as the input, if available, if not then the existing asset database to retrieve a yearly cross-asset MR&R treatment plan for a specified budget. The designed model will consider the input as follows:

i) Sections identified by the asset-specific proprietary models for the respective asset types, if available; if not, the asset inventory database (Path II as shown in the Figure 8). The inputs are completely dependent on the decision maker as s/he may disregard the results from the proprietary models and instead use the entire asset database (Path I as shown in the Figure 8).

ii) The condition function for each asset to calculate the yearly failure probability.

iii) Yearly funding available for the treatment of sections

5.4. Application of the model in the City's asset database

5.4.1. Modeling the linear assets

Data Available from the City's Water Mains database:

i) Break Rate Equation (Rate of Failure Function) for different Cohorts.

ii) The Age, Material, Diameter, Length, and Cost of replacement of various assets in the Water Mains.

iii) The Consequence of Failure (COF) for various Water Main Assets.

The given condition function for the water mains is:

$$\text{Condition} = \text{constant} \times e^{\text{slope} \times t}$$

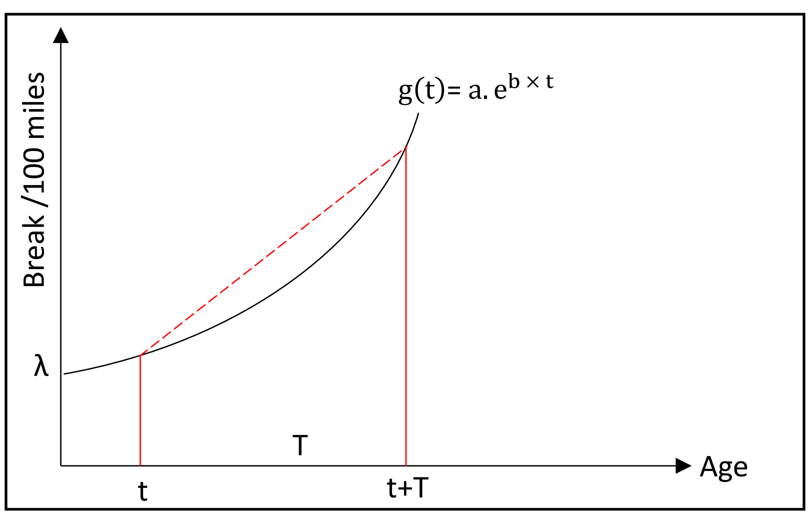


Figure 11: Expected Condition Function for Water Mains

i.e, $g(t) = a.e^{b \times t}$

where,

t = initial age of the pipe

T = analysis period (10 years)

g(t) = expected condition performance

function (rate of failures per year)

Linearizing the condition function as shown in figure 12,

$$\lambda_1(t_0) = g(t_0)$$

$$\lambda_2(t_0 + T) = \frac{g(t_0 + T) - g(t_0)}{T}$$

$$f(x) = g(t_0) + \left(\frac{g(t_0 + T) - g(t_0)}{T}\right) \times x$$

which is in the form of:

$$f(x) = \lambda_1 + \lambda_2 x$$

Therefore,

$F(x) = \int_{t=0}^{T} (\lambda_1 + \lambda_2 x)dx$ is the probability of failure F(t).

From the equation above, the probability of failure is a function of age and the length of the pipes. However, the length of segments in water mains ranges from 1 ft. to 8000 ft. If the failure probability for the segments is calculated using this actual length, the segments with lengths in hundreds and thousands will have a high probability of failure, and the sections with the length in tens or unit digits of feet will have an extremely low probability of failure, irrespective of the age. Therefore, the failure probability is calculated by dividing the pipes into homogenous sections of length 1000 ft., where the expected number of failures is the binomial expectation. The expectation is based on the assumption that the expected number of failures for

1000 ft. should be the same as the sum of the expected number of failures of many smaller sections adding to 1000 ft.

The table below shows the calculation of expected number of failures in a sample 8 in. diameter AC pipes with total length 1320.8 ft. in the 10th year. The break rate is calculated using the condition function used by the city for AC pipes. The constants λ_1 and λ_2 are calculated by linearizing the break rate function. The failure probability and the expected number of failures are calculated assuming each segment to behave as a 1000ft. homogenous sections.

Table 17: Calculation of expected failure in sample AC pipes in 10th year

Age	Dia.	Material	Length	Const.	Slope	Break rate (t)	Break rate (t+10)	λ1	λ2	F(10)	E(f)
39	8	AC	412.97	8	0.0384	35.768	52.512	0.068	0.003	0.836	0.345
39	8	AC	163.79	8	0.0384	35.768	52.512	0.068	0.003	0.836	0.137
33	8	AC	341.19	8	0.0384	28.407	41.706	0.054	0.003	0.664	0.227
38	8	AC	220.47	8	0.0384	34.420	50.534	0.065	0.003	0.804	0.177
39	8	AC	161.30	8	0.0384	35.768	52.512	0.068	0.003	0.836	0.135
36	8	AC	21.07	8	0.0384	31.876	46.798	0.060	0.003	0.745	0.016
Tot.			1320.8								1.037

The expected number of failures in each section is the product of its length and the respective failure probability in that particular year. The total expected number of failures is the sum of expected failures in each section in a particular year. From the table we can see that the total expected number of failures in the network of sample AC pipe is 1.037 per 1000 ft. in the 10th year. The tables below show the yearly total expected cumulative and annual failures per 1000 ft. in the water mains network, respectively.

Table 18: Expected Cumulative Failures over 10 years in the Water Mains network

Year	Expected Cumulative failures per 1000 ft.					
	AC	PVC	CI	DIP	STL	Total
0	0	0	0	0	0	0
1	57.09371	32.25267	2.189001	4.79E-02	1.95E-02	91.6028
2	116.8055	66.66814	4.502555	9.86E-02	4.01E-02	188.1148
3	179.1352	103.2464	6.940663	0.151915	6.18E-02	289.5361
4	244.0831	141.9875	9.503324	0.208006	8.47E-02	395.8665
5	311.6489	182.8913	12.19054	0.266823	0.108601	507.1062
6	381.8328	225.958	15.00231	0.328366	0.13365	623.2551
7	454.6347	271.1874	17.93863	0.392635	0.159809	744.3133
8	530.0547	318.5797	20.9995	0.459631	0.187077	870.2806
9	608.0927	368.1347	24.18493	0.529352	0.215455	1001.157
10	688.7487	419.8526	27.49491	0.6018	0.244943	1136.943

Table 19: Expected Annual Failures over 10 years in the Water Mains network

Year	Expected Annual failures per 1000 ft.					
	AC	PVC	CI	DIP	STL	Total
0	0	0	0	0	0	0
1	57.09371	32.25267	2.189001	4.79E-02	1.95E-02	91.6028
2	59.71175	34.41547	2.313554	5.06E-02	2.06E-02	96.51202
3	62.32978	36.57827	2.438108	0.053365	2.17E-02	101.4212
4	64.94782	38.74106	2.562661	0.056091	2.28E-02	106.3305
5	67.56586	40.90386	2.687215	0.058817	0.023939	111.2397
6	70.18389	43.06666	2.811768	0.061543	0.025049	116.1489
7	72.80193	45.22946	2.936322	0.064269	0.026159	121.0581
8	75.41997	47.39225	3.060875	0.066995	0.027268	125.9674
9	78.038	49.55505	3.185428	0.069722	0.028378	130.8766
10	80.65604	51.71785	3.309982	0.072448	0.029487	135.7858

5.4.2. Modeling the point assets

Data available from the City's database:

i) The age, type, size, and cost of replacement of various assets in the lift stations.

ii) The condition functions for various assets in the lift stations.

iii) The COF and LOF for the assets in the lift stations.

The effective age of assets in the lift station is based on the condition equation used by the city. The condition equation below, provided by the city, evaluates the LOF for the assets which is used to evaluate their effective age.

$$\text{Condition} = (\text{slope} \times \text{age}) - \text{Y intercept}$$

Table 20: Condition score and their description

Condition	Description
1	Very Good
2	Minor Defects only
3	Maintenance Required
4	Requires Repair
5	Asset Unserviceable

The table below shows the condition equation and the parameters used by the city for the various assets in the lift station.

Table 21: Parameters of condition equation for the Lift Station assets

Asset	EUL	Y-Intercept	Slope	Condition equation
Odor Control	10	1	0.4	$\text{Condition} = (\text{slope} \times \text{age}) - \text{Y intercept}$
Portable Bypass Pump	10	1	0.4	
SCADA	10	1	0.4	
Grounds	15	1	0.26667	
Pipes	15	1	0.26667	
Valves	15	1	0.26667	
Blowers	20	1	0.2	
Controls	20	1	0.2	
Generators ATS	20	1	0.2	
Stationary Bypass Pump	20	1	0.2	
Sub Grinder Pump	20	1	0.2	
Submersible Pump	20	1	0.2	
Self-Priming Pump	25	1	0.16	
Wet Wells	25	1	0.16	

The effective age for the asset is calculated by plotting the condition curve for the asset with condition in Y- axis and Age in X- axis, followed by projecting a straight line from the LOF toward the condition curve and projecting vertically towards x-axis as shown in the figure below.

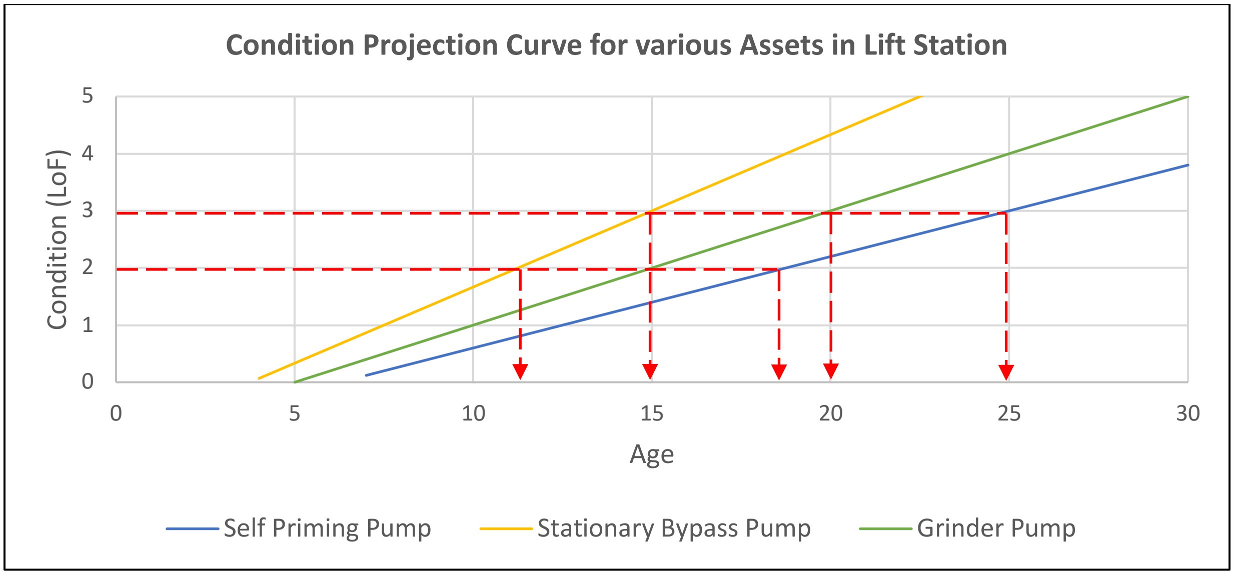


Figure 12: Condition projection curve for the assets in the lift station

From the figure, the effective age of the grinder pump, stationary bypass pump, and self-priming pump with the likelihood of failure 2 are 15, 12, and 19 years, respectively.

The table below provides similar examples of the calculation of effective age of the assets from the condition curve and likelihood of failure.

Table 22: Calculation of the effective age using the condition equation

Asset Type	Condition (LOF)	Effective Age (years)
Grinder Pump	2	15
Grinder Pump	3	20
S. Bypass Pump	2	12
S. Bypass Pump	3	15
Self-Priming Pump	2	19
Self-Priming Pump	3	25

The failure prediction of the assets in the lift station is evaluated using a 2-parameter Weibull distribution. Failure is a function of the shape (β) and the scale (η) parameters, which are estimated using the estimated useful life and coefficient of variation. In this project, the coefficient of variation for all the assets is assumed to be 20%. The table below provides the effective age of the assets based on their likelihood of failure.

Table 23: Effective Age of the assets based on the LOF

Assets	LOF	Effective Age	EUL	CoV
Odor Controls, Portable Bypass Pump, SCADA	1	5	10	20%
	2	8		
	3	10		
	4	13		
	5	15		
Grounds, Pipes, Valves	1	8	15	20%
	2	12		
	3	15		
	4	19		
	5	23		
Blowers, Controls, Generators, Submersible / Grinder Pumps	1	10	20	20%
	2	15		
	3	20		
	4	25		
	5	30		
Wet Well, Self-Priming Pump	1	13	25	20%
	2	19		
	3	25		
	4	32		
	5	38		

The EUL and COV of the assets are used to estimate the parameters of the 2-parameter Weibull distribution as discussed in the methodology. The estimated parameters are then used with effective ages of the assets to calculate their conditional reliability over time. The Weibull conditional reliability function provides the best estimate of the upcoming failures as it accounts for the survival of the asset prior to the forecast. To further illustrate that, the figures below show the change in the probability density functions of the assets given that they survive a specific age. The specific ages for the assets are their effective ages. Despite the height of density function increases with the survival or the effective age of the assets, the area under the curve is always equal to 1 for all the cases.

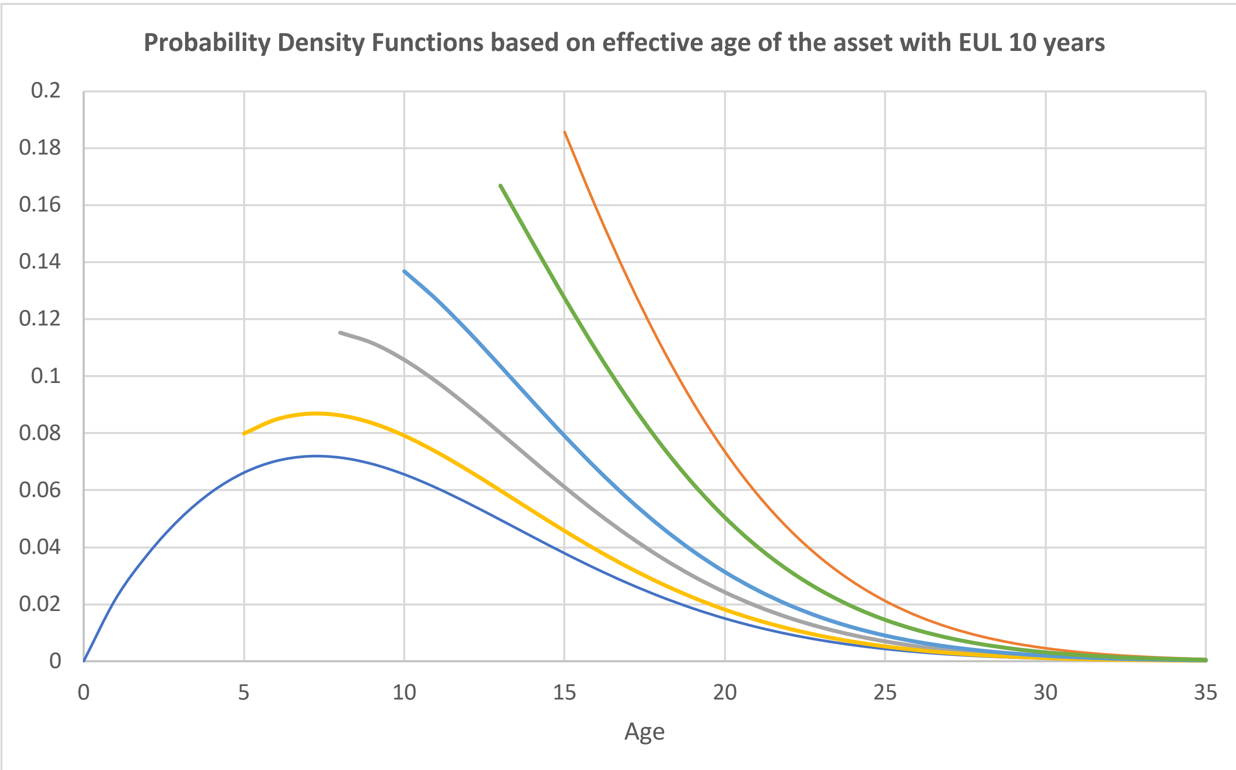


Figure 13: Probability density functions based on the effective ages of the assets with EUL 10 years

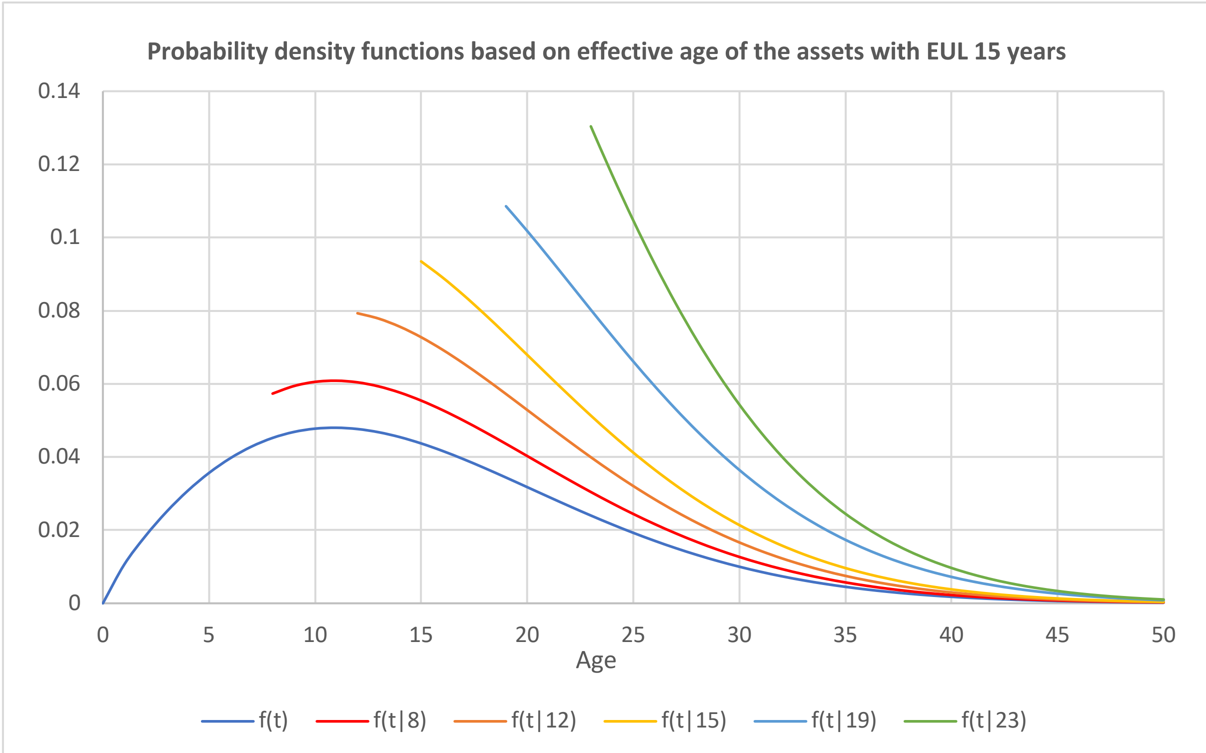


Figure 15: Probability density functions based on the effective ages of the assets with EUL 15 years

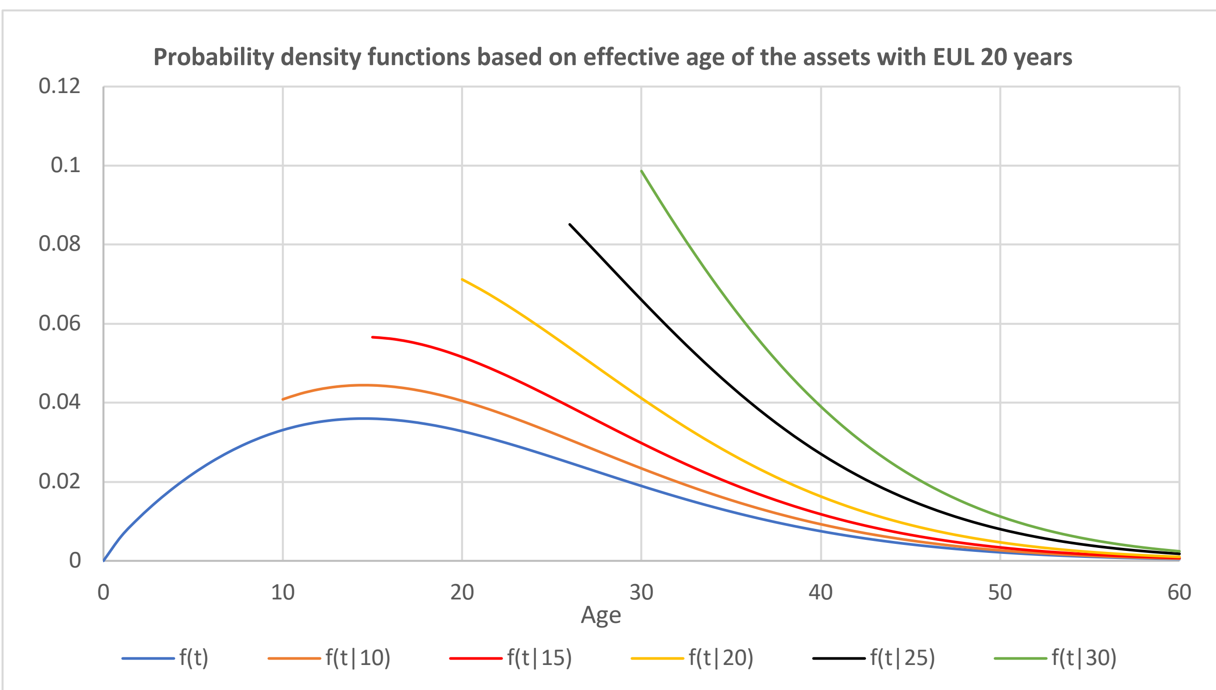


Figure 14: Probability density functions based on the effective ages of the assets with EUL 20 years

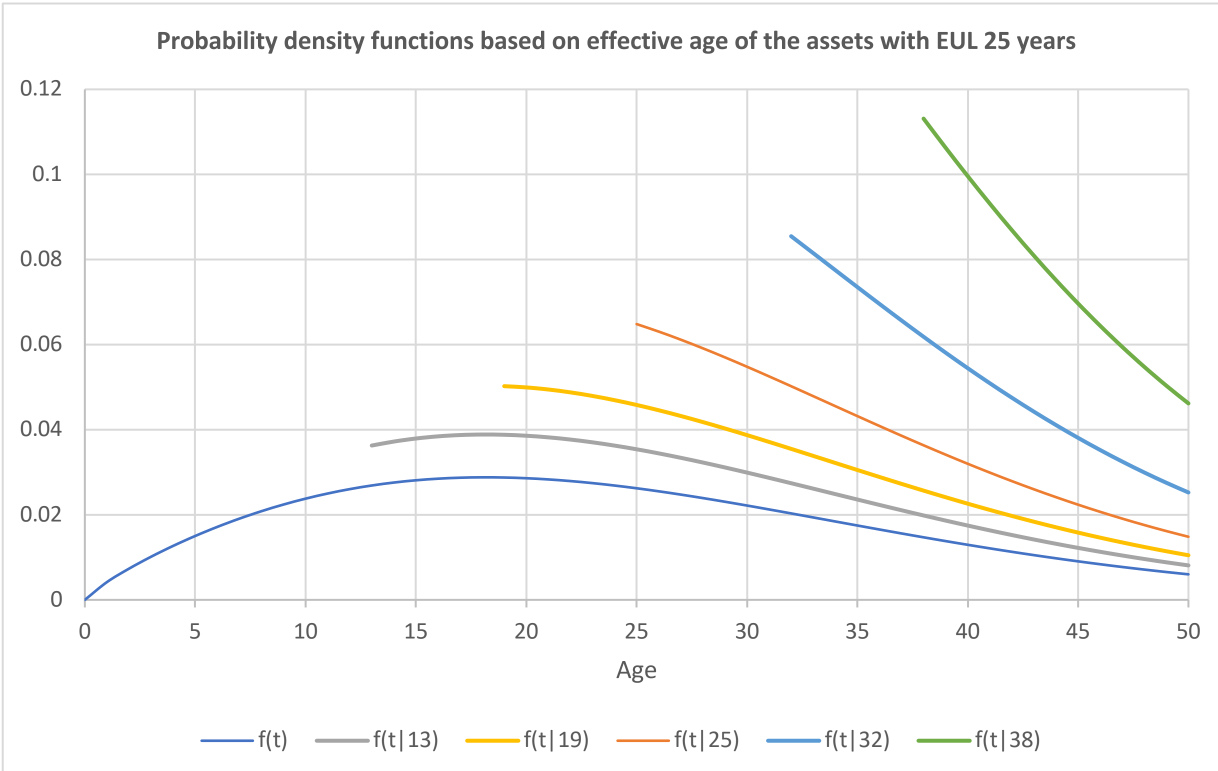
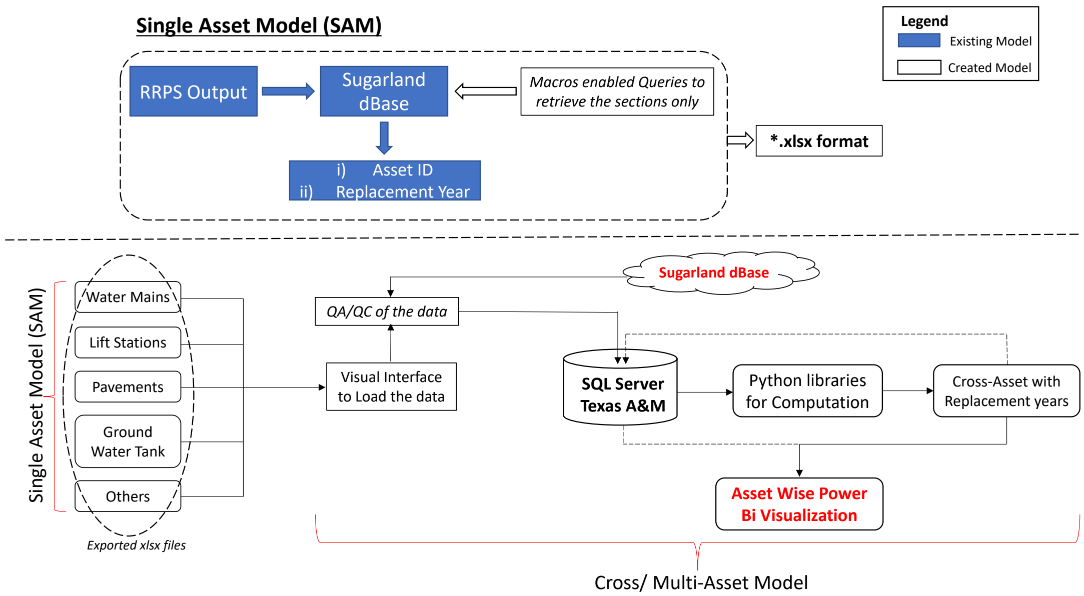


Figure 16: Probability density functions based on the effective ages of the assets with EUL 25 years

5.5. Integrated Asset Management System (IAMS) model for the City of Sugar Land, TX

The results from the single asset models are exported using macro-enabled queries to get the list of sections with the replacement year, and the asset inventory is imported to the designed model using a Visual Basic Interface. The interface allows the user to load all the data into a SQL server, making it a cross-asset model. The SQL server is built the library functions from Python to compute the failure probabilities, map the failure probabilities with the COF and the asset's replacement cost to calculate the yearly BCP number. Furthermore, the server also provides the sections for the replacement prioritized using the yearly BCP number. The output from the model is linked with Microsoft Power-Bi to generate and visualize the results. The figure below shows the process model for the integrated asset management system.



Note: RRPS is the City's proprietary model called Rehabilitation and Replacement Planning System for Water Mains and Lift Stations.

Figure 17: Process Model for the Integrated Asset Management System (IAMS)

The figure below shows the flowchart of the designed IAMS model.

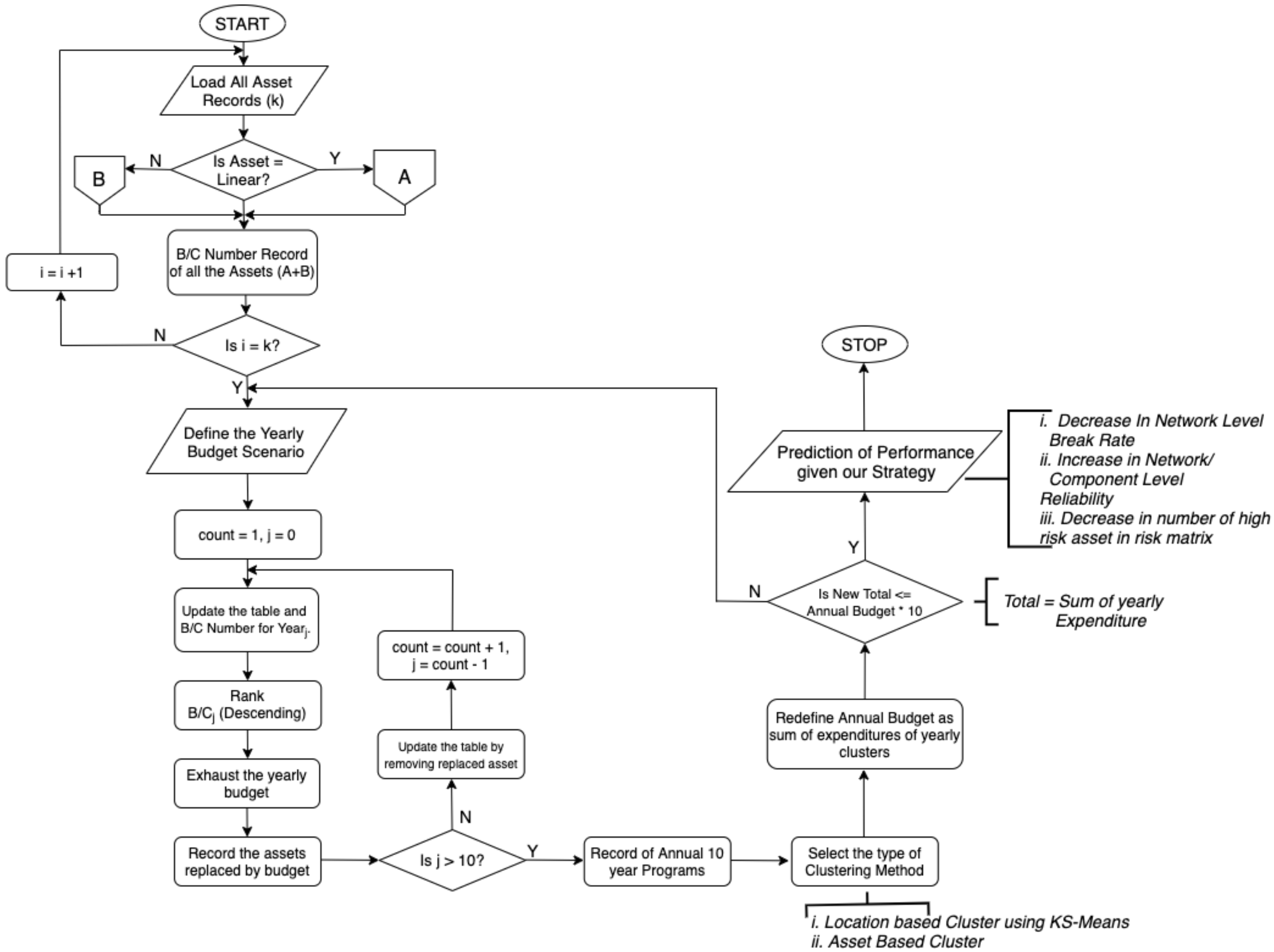


Figure 18: Flow model for the Integrated Asset Management System model

1. Firstly, the user loads all the required data into the SQL server.
2. The model then checks if an asset belongs to the linear or the point category.
3. If linear, the model calls for the yearly BCP number of all the assets from the linear asset model and stores them in a table. Similarly, for point assets, the model calls the point asset model and store the results of the yearly BCP number in a table.
4. After the calculation of the yearly BCP number is done for all the assets, the model combines the tables of linear and points assets and checks for the user-defined yearly budget scenario.

5. The assets are then ranked by the first year BCP number in decreasing order and selected for replacement as 1st year program until supported by the budget.
6. Step 5 is repeated with ranking the remaining sections by next year's BCP number and selected for replacement as next year's program until supported by the budget.
7. The selected sections are clustered into groups based on their spatial coordinates or the asset type to plan the annual replacement programs.
8. The model finally shows the projected performance of the assets at the network level. The performances include:
    i. A decrease in the network level break rate or the number of failures in linear assets.
    ii. Increase in the average reliability of the network in point assets.
    iii. A decrease in the number of assets in a very high- and high-risk category in both linear and point assets.

The IAMS model is designed with a set of queries that calculates the yearly BCP number of linear assets and point assets separately. Once the model identifies the asset type as a linear, it processes the workflow for the linear asset model as discussed below:

1. The user imports the asset data for the linear assets into the IAMS model, and the model calls for the queries designed for the linear asset model to calculate the yearly BCP number.
2. The user specifies the scale factor to be used to calculate the consequence of failure. The scale factors are the multiplier used to quantitatively access the consequence of failure. The model uses the scale factor of 1 as default to evaluate the COF. The scale factor 1 uses the default values of the COF as it is from the database.

3. If the assets have an existing proprietary model (e.g., Water Mains), the model calculates the failure probabilities, and yearly BCP number of the sections retrieved by the existing model (Path I); if not, the model calculates the failure probabilities and yearly BCP number of all sections (Path II).
   i. The example below shows the calculation of the yearly BCP number of the sections in Water Mains without using the existing proprietary model provided by the proprietary model.
   ii. Linearize the condition equation for the given length to determine the constants λ1 and λ2.
   iii. Determine the failure density for the specific pipe segment.
   iv. Determine the failure probability for the pipe segment.
   v. Estimate the yearly number of failures in the pipe segment over time.
   vi. Aggregate the yearly number of failures for all pipe segments overtime to get the cumulative and annual failures in the water mains network over time.
   vii. Determine the yearly BCP number for each pipe segment and retrieve the results into the main model.

The figure below shows the flowchart of the linear asset model using the example of Water Mains.

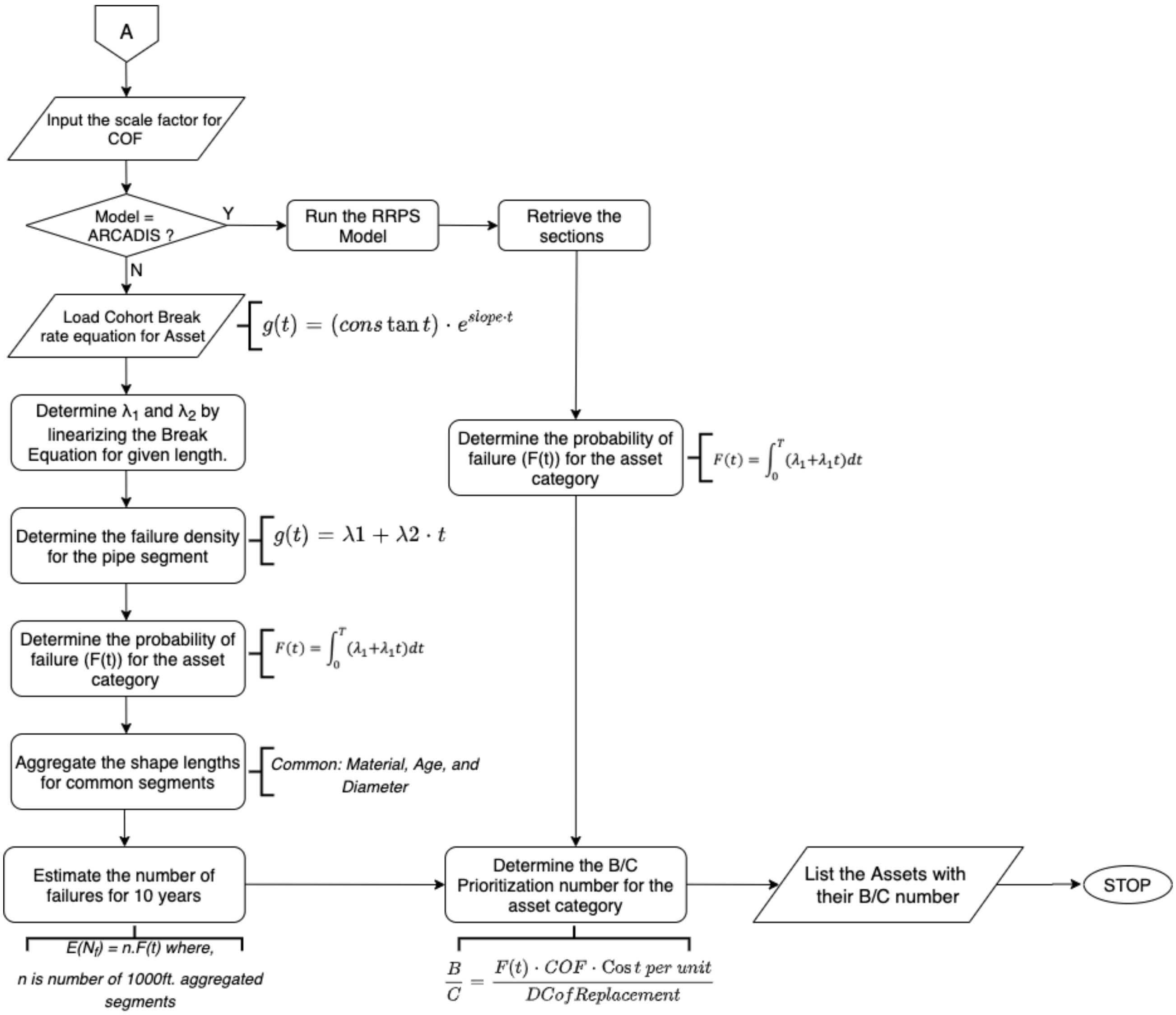


Figure 19: Flowchart for the linear model using the example of Water Mains

If the model identifies the asset type as a point, it processes the workflow for the point asset model as discussed below:

1. The user imports the asset data for the point assets into the IAMS model, and the model calls for the queries designed for the point asset model to calculate the yearly BCP number.
2. The user specifies the scale factor to be used to calculate the consequence of failure. The scale factors are the multiplier used to quantitatively access the consequence of failure. The model uses the scale factor of 1 as default to evaluating the consequence of failure.
3. If the assets have an existing proprietary model (e.g., Lift Stations), the model calculates the conditional reliabilities, failure probabilities, and yearly BCP number of the sections retrieved by the existing model (Path I); if not, the model calculates the failure probabilities and yearly BCP number of all sections (Path II).

   The example below shows the calculation of the yearly BCP number of the assets in the Lift Stations without using the existing proprietary model provided by the City of Sugar Land.

   i. Load the condition function for the assets and determine the effective age of the assets from the LOF scores.
   ii. Estimate the shape and scale parameters of the 2-parameters Weibull distribution using the estimated end useful life of the asset and coefficient of variation as 20%.
   iii. Estimate the reliability, and failure probability using the survival analysis for the Weibull distribution.
   iv. Determine the yearly BCP number for each asset and retrieve the results into the main model.

The figure below shows the flowchart of the point asset model using the example of the lift stations assets.

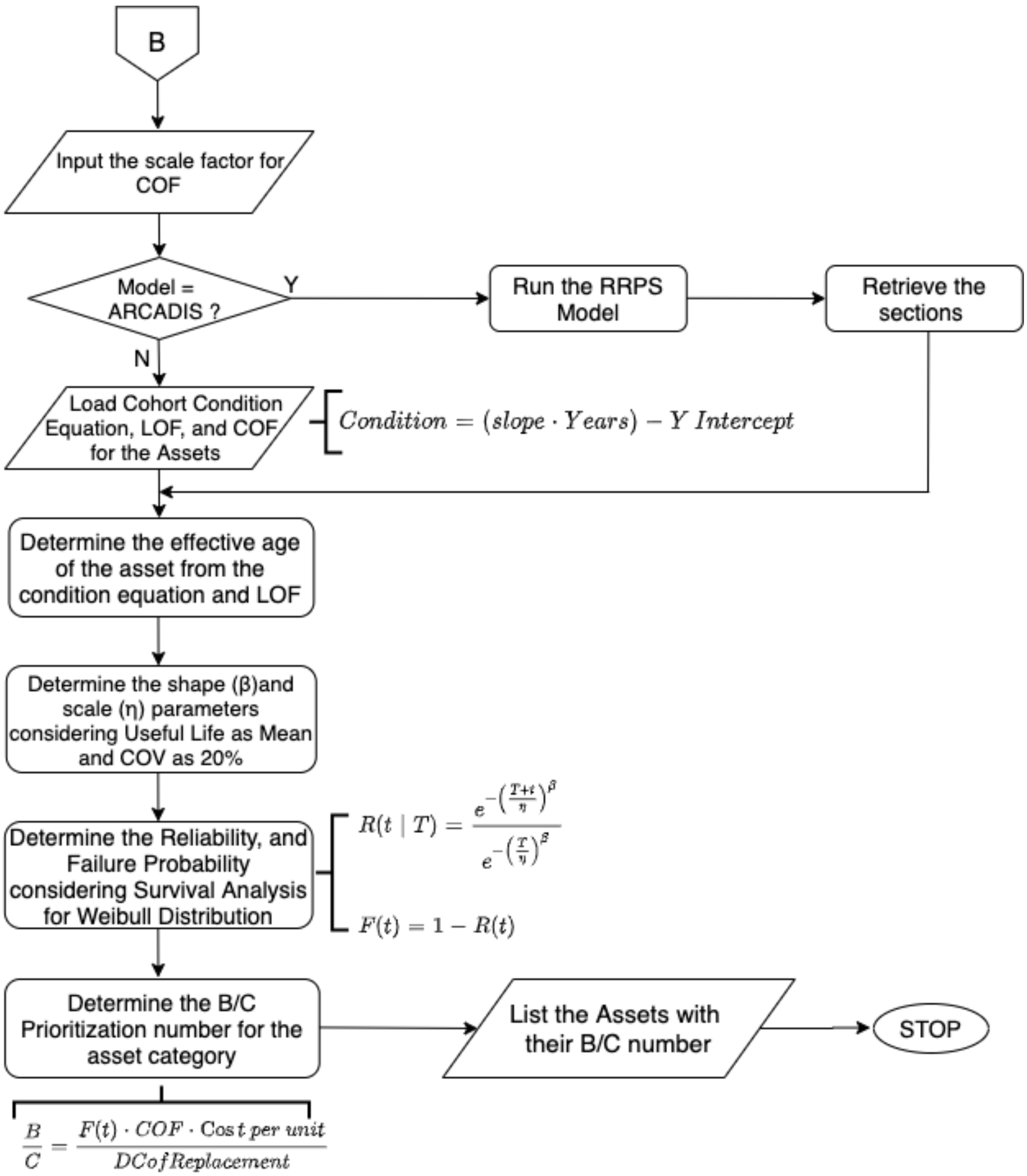


Figure 20: Flowchart for the linear model using the example of Lift Stations

5.6. Prioritization Strategies for the Preventive Maintenance

After analyzing the asset inventory data and applying the methodology of the discussed model, the obtained results are shown in this section. Several tables and plots are presented to analyze and visualize the results from the model. Similarly, three different strategies are presented to visualize the differences in the outcomes. The strategies compared and presented in this section are risk-based prioritization, asset-based prioritization, and location-based prioritization for water mains and lift station assets.

5.6.1. Risk-based Prioritization

Risk-based prioritization deals with replacing the sections with the highest yearly BCP number. The yearly failure probabilities of each asset are calculated based on their condition parameters. The yearly failure probabilities multiplied with the expected failure consequences value gives the yearly BCP number. Firstly, for any specified budget scenario, the sections are sorted according to their first year BCP number. The sections with the highest values are replaced until the budget for the first year is exhausted. The remaining sections are sorted according to their second year BCP number and replaced until the budget for that year is exhausted. The process is repeated for the number of years specified by the decision-maker. The table below shows the result of the risk-based prioritization using a yearly budget of $5.0 million for 10 years.

Table 24: Risk based prioritization results for the yearly budget of $5.0 m for 10 years

Asset Category	Total Assets Replaced	Total Expenditure	Replacement Year
Water Mains	7	$283,240	**1**
Lift Stations	128	$4,712,300.00	
Total	**135**	**$4,995,540**	
Water Mains	8	$552,583	**2**
Lift Stations	91	$4,234,200.00	
Total	**99**	**$4,786,783**	

Table 24: Continued

Asset Category	Total Assets Replaced	Total Expenditure	Replacement Year
Water Mains	10	$1,019,480	**3**
Lift Stations	133	$4,178,300.00	
Total	**143**	**$5,197,780**	
Water Mains	27	$2,053,531	**4**
Lift Stations	78	$2,725,400.00	
Total	**105**	**$4,778,931**	
Water Mains	11	$473,147	**5**
Lift Stations	139	$4,705,800.00	
Total	**150**	**$5,178,947**	
Water Mains	93	$3,417,411	**6**
Lift Stations	30	$1,359,400.00	
Total	**123**	**$4,776,811**	
Water Mains	63	$3,344,764	**7**
Lift Stations	45	$1,831,800.00	
Total	**108**	**$5,196,564**	
Water Mains	151	$4,700,790	**8**
Lift Stations	0	$0	
Total	**151**	**$4,700,790**	
Water Mains	129	$4,606,629	**9**
Lift Stations	25	$691,800.00	
Total	**154**	**$5,298,429**	
Water Mains	88	$4,671,581	**10**
Lift Stations	0	$0	
Total	**88**	**$4,671,581**	

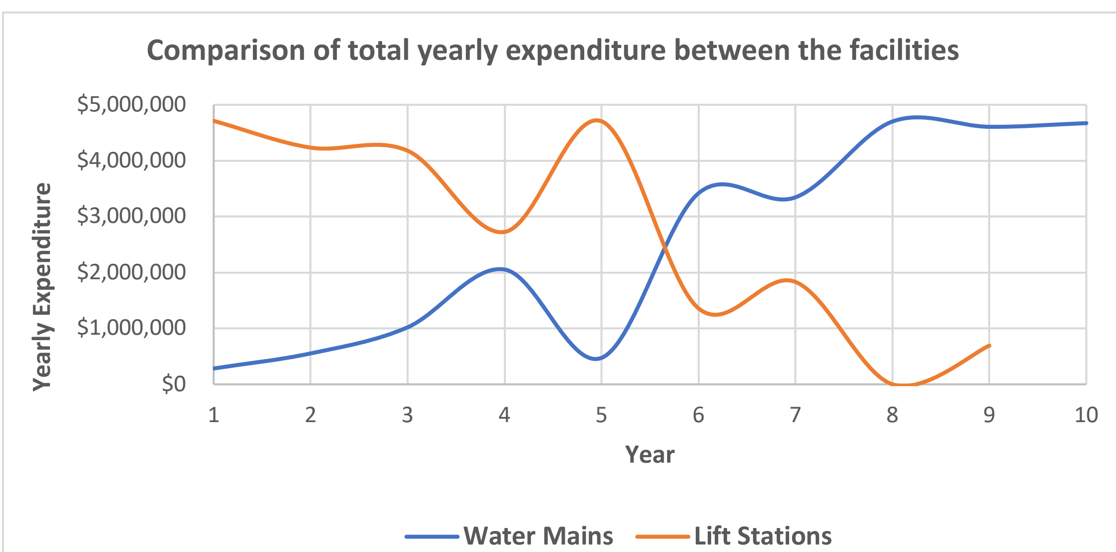


Figure 21: Comparison of the yearly expenditure between the facilities

The figure above shows the distribution of yearly expenditures between the water mains and lift stations. From the figure above, we can see that lift stations are initially prioritized for replacement over the water mains because most of the assets in lift stations such as SCADA, odor controls, and portable bypass pumps have an estimated life of ten years, resulting in a higher probability of failures. Furthermore, other reasons could be a higher value of COF associated with the failure of these assets. To interpret the results better, the tables below provide the results of Water Mains in terms of the risk matrix.

Table 25: Risk Matrix for the Water Mains at present

Current Condition for the Water Mains					
	1 (VL)	2 (L)	3 (M)	4 (H)	5 (VH)
1 (VL)	328.03	13.97	97.26	7.43	1.25
2 (L)	96.29	1.89	39.02	3.39	0.03
3 (M)	28.06	0.62	2.94	0.19	0.17
4 (H)	18.34	0.28	2.8	0.18	0.02
5 (VH)	7.86		0.14		

Table 26: Risk Matrix for the Water Mains if nothing is done for 10 years

Do Nothing for next 10 years					
	1 (VL)	2 (L)	3 (M)	4 (H)	5 (VH)
1 (VL)	263.29	78.71	13.58	80.3	12.07
2 (L)	72.66	22.3	9.04	30.26	6.37
3 (M)	23.47	3.96	0.66	3.33	0.55
4 (H)	14.51	3.95	1.11	1.85	0.2
5 (VH)	7.34	0.52	0.05	0.09	

Table 27: Risk Matrix for the Water Mains after 10 years of Cross-Asset Maintenance

After 10 years of the Cross-Asset Preventive Maintenance					
	1 (VL)	2 (L)	3 (M)	4 (H)	5 (VH)
1 (VL)	263.3	78.71	13.58	80.3	12.07
2 (L)	89.1	22.34	9.04	18.86	1.29
3 (M)	26.24	4.32	0.17	1.24	
4 (H)	16.37	4.95	0.13	0.16	
5 (VH)	7.59	0.4			

Similarly, the tables below provide the results of Lift Stations in terms of the risk matrix.

Table 28: Risk Matrix for the Lift Stations at present

Current Condition for the Lift Stations					
	1 (VL)	2 (L)	3 (M)	4 (H)	5 (VH)
1 (VL)		8	2		16
2 (L)		113	48	39	35
3 (M)	15	212	152	118	139
4 (H)	7	64	49	43	42
5 (VH)		13	5	5	1

Table 29: Risk Matrix for the Lift Stations if nothing is done for 10 years

Do Nothing for next 10 years					
	1 (VL)	2 (L)	3 (M)	4 (H)	5 (VH)
1 (VL)				5	21
2 (L)				43	192
3 (M)			12	87	537
4 (H)			4	29	172
5 (VH)				7	17

Table 30: Risk Matrix for the Lift Stations after 10 years of Cross-Asset Maintenance

After 10 years of the Cross-Asset Preventive Maintenance					
	1 (VL)	2 (L)	3 (M)	4 (H)	5 (VH)
1 (VL)				5	21
2 (L)		6	4	43	182
3 (M)	194	229	36	84	93
4 (H)	117	66	6		16
5 (VH)	14	7	3		

While the risk-based prioritization provides the sections for replacement based on the yearly BCP number, the approach does not account for the economies of scale, i.e., location and the type of assets for prioritization. Since the model is dependent on the yearly budget, there is a higher likelihood for the city to work in the same area every alternate year because of the insufficient budget. For example, two similar pipes with the same benefits at the same location or two similar pumps with the same benefits at the same lift station could be prioritized to be replaced in different years because of the insufficient budget. However, this problem can be solved using an asset-based prioritization or a location-based prioritization strategy. In this project, we consider both the strategies as viable ones for the lift stations but only location-based for the water mains because of the limited asset types in the water mains, i.e., AC and PVC.

5.6.2. Asset-based Prioritization

Asset-based prioritization primarily deals with replacing all the assets of a particular type in a specific year. The prioritization is based on the average replacement age of all the assets in a particular group. The main aim of asset-based prioritization is that it provides the management with an opportunity to outsource the replacement by accepting the lowest bids. In other words, it provides the flexibility to the managers to find a contractor who provides the best offer for the maintenance of a particular group and replace/maintain it. The table below provides the results of asset-based prioritization for replacement in the lift stations.

Table 31: Asset based prioritization of the lift stations

Cluster	Asset Type	Average B/C	Total Cost	Average Replacement Yr.	Number of Assets
7	Controls	1.026384	$6,998,000	4.49	99
3	Generator ATS	1.006997	$254,000	4	3
6	Grounds	0.873572	$2,928,000	3.31	87
1	Odor Control	0.586414	$376,000	1	2
9	Pipes	0.845903	$767,600	3.4	96
1	Portable Bypass Pump	0.569614	$89,000	1	1
4	SCADA	0.537136	$875,000	1.49	35
5	Stationary Bypass Pump	0.808119	$3,278,000	2.93	30
8	Sub	0.863736	$5,897,800	3.48	181
3	Sub Grinder	1.024687	$87,400	4.2	5
10	Valves	0.866846	$1,851,200	3.41	96
2	Wet Well	1.356569	$1,057,000	7.21	34

Table 32: Results of the asset-based prioritization of the lift stations

Cluster	Asset Type	Average B/C	Total Cost	Average Replacement Yr.	Number of Assets
1	Odor Control, Portable Bypass Pump	0.578014	$465,000	1	3
4	SCADA	0.537136	$875,000	1.49	35
5	Stationary Bypass Pump	0.808119	$3,278,000	2.93	30
6	Grounds	0.873572	$2,928,000	3.31	87
9	Pipes	0.845903	$767,600	3.4	96
10	Valves	0.866846	$1,851,200	3.41	96
8	Submersible Pump	0.863736	$5,897,800	3.48	181
3	Generator ATS, Sub Grinder Pump	1.015842	$341,400	4.1	8
7	Controls	1.026384	$6,998,000	4.49	99
2	Wet Well	1.356569	$1,057,000	7.21	34

The results from the table 32 show that the maximum reduction in the risk or maximum benefit is achieved if all the Odor Controls, Portable Bypass are replaced first, followed by the SCADA, Pumps, and ultimately Wet Wells. Since the risk associated with an asset's failure is a function of its direct and indirect cost, given that the direct cost is an independent variable, replacing the assets in the ascending order of the average replacement year as shown in the table above will ensure a maximum reduction in the indirect cost.

5.6.3. Location-based Prioritization

Location-based prioritization is a clustering approach of dividing the assets into groups around a specific location and allotting them into the same group using K-means clustering algorithms. K-means clustering is a centroid-based approach to partition the dataset, where k is the number of user-specified centroids or the division, and means is the averaging method to determine the location of the centroid. In this project, the coordinates of the assets are assumed to be point-shape files and are calculated using the GIS. Then, the decision-maker defines the number of required clusters based on the number of projects they want. The clusters are calculated as the sum of squared distances Euclidean distances between items and the corresponding centroid. Each data point is assigned to a given cluster such that the sum of squares distance of the observation to their assigned cluster centers is minimized. The clustering in this project is performed using Power-Bi which uses the syntax of R programming. The table below shows the location-based prioritization of the water mains and lift stations respectively.

Table 33: Location based prioritization of the Water Mains using K-Means

Clusters	Miles replaced	Average B/C	Average Year	Total Cost	Index
Cluster10	0.207201	0.99104	4	$191,377	
Cluster6	5.639085	1.330976	6.91	$5,833,616	
Cluster9	2.75825	1.31633	6.95	$2,780,442	
Cluster4	4.197629	1.36198	7.06	$4,953,275	
Cluster3	0.85393	1.392482	7.5	$747,297	
Cluster8	0.75106	1.423964	7.92	$841,892	
Cluster5	2.374085	1.436877	7.98	$2,633,505	
Cluster1	1.365803	1.445033	8.04	$1,439,399	
Cluster2	3.985614	1.485981	8.29	$4,748,672	
Cluster7	0.782909	1.569405	9.28	$953,681	

Table 34: Location based prioritization of the Lift Stations using K-Means

Clusters	Assets Replaced	Average of B/C	Average Year	Total Cost	Index
Cluster3	59	0.809177	3.05	$2,404,400	
Cluster10	29	0.786746	3.14	$968,800	
Cluster7	65	0.817758	3.15	$1,917,000	
Cluster9	75	0.845408	3.39	$2,315,400	
Cluster1	98	0.86976	3.54	$2,746,000	
Cluster6	73	0.892256	3.6	$3,162,900	
Cluster5	43	0.907259	3.72	$1,807,600	
Cluster2	94	0.9363	3.86	$4,359,600	
Cluster4	69	0.987406	4.22	$2,593,900	
Cluster8	64	1.012236	4.41	$2,183,400	

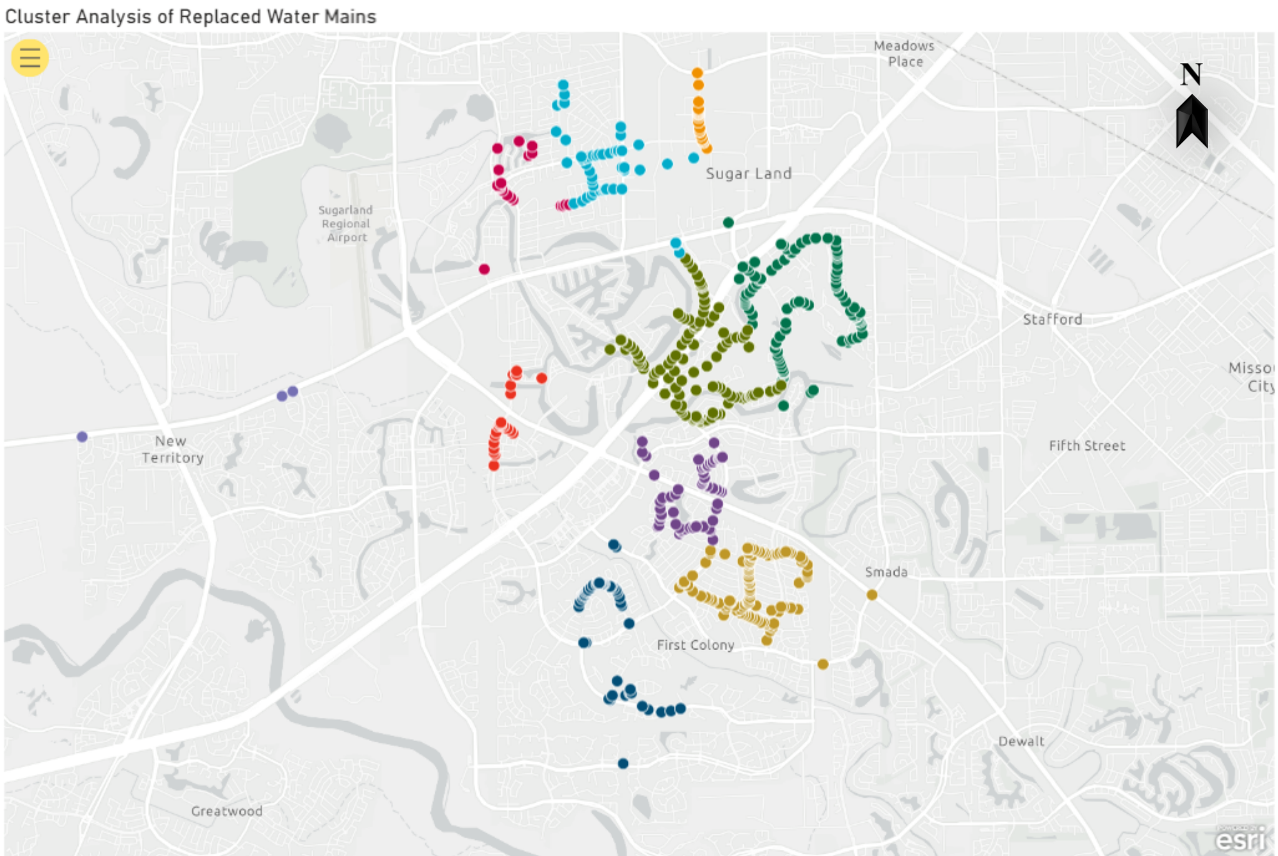


Figure 22: Location based clustering of Water Mains using k-means approach

The figure above shows the spatial clustering of the water mains assets identified by the model for replacement using the K-means approach. The results of the model shown were run considering the assets in water mains and the lift stations with a yearly budget scenario of $5.0 million for 10 years.

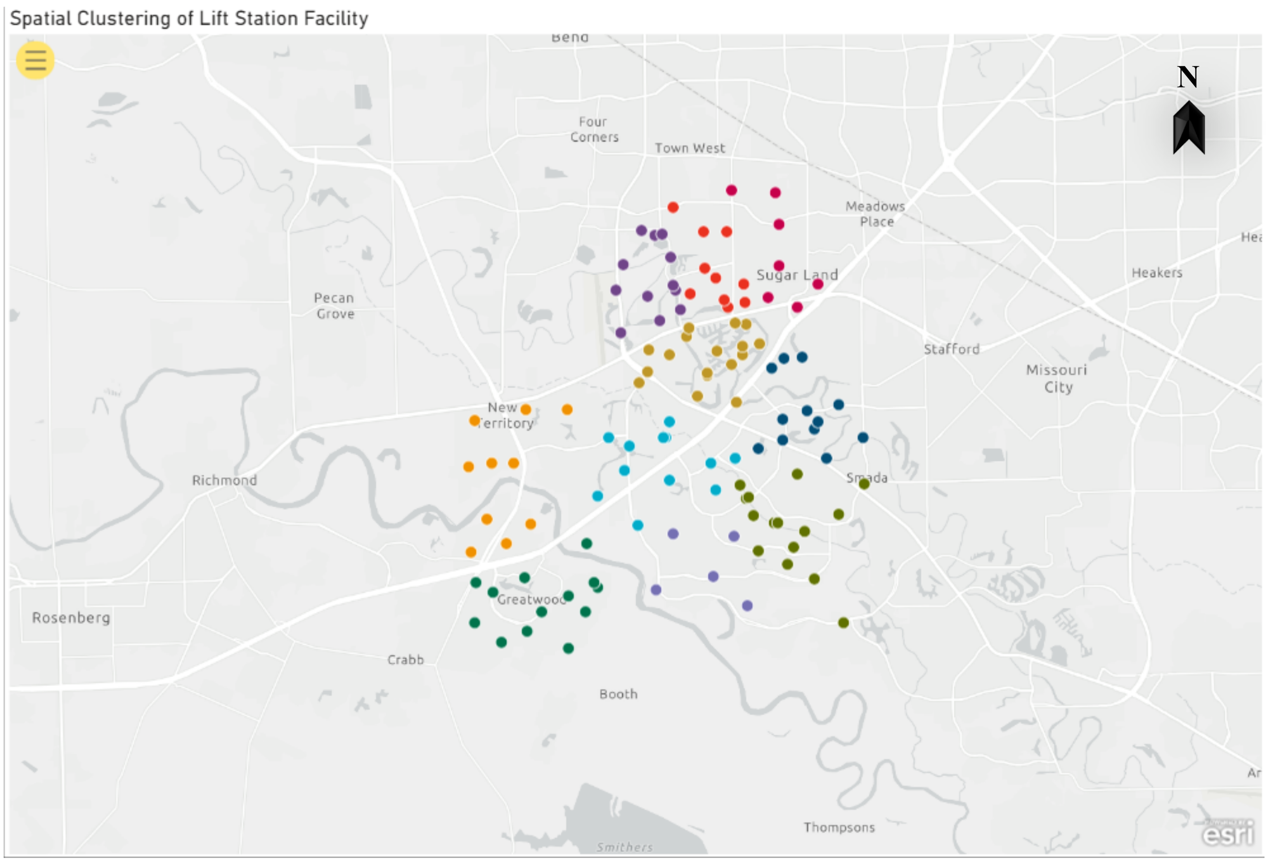


Figure 23: Location based clustering of Lift Stations using k-means approach

The figure above shows the spatial clustering of the lift station assets identified by the model for replacement using the K-means approach. The results of the model shown were run considering the assets in water mains and the lift stations with a yearly budget scenario of $5.0 million for 10 years.

6. RESULTS AND DISCUSSIONS

This chapter interprets and discusses the results of the developed model on the asset database of the City of Sugar Land, TX. It further analyzes whether the primary objective of the research, i.e., to develop a framework that evaluates risk in the multiple assets, prioritize them in terms of their benefit of replacement, and allocate the replacement budget, has been achieved or not. The results of the model are analyzed using the comparison of outputs between the two-yearly budget scenarios of \$3.0 million and \$5.0 million for 10 years in terms of the following:

i. A decrease in the number of assets in a very high- and high-risk category in both linear and point assets.
ii. A decrease in the network level break rate or the number of failures in linear assets.
iii. An increase in the average reliability of the network in point assets.

6.1. Comparative analysis of the results using two funding scenarios

The table below shows the comparison of the results of the risk-based prioritization using two-yearly budget scenarios of \$3.0 million (A) and \$5.0 million (B) for 10 years. It can be seen that the total number of assets replaced each year increases with the increase in the yearly budget. While the total number of assets replaced with the yearly budget of \$3.0 million for 10 years is 746, the total number of assets replaced with the yearly budget of \$5.0 million for 10 years is 1256.

Table 35: Comparative analysis of results of \$3.0m and \$5.0m yearly budget scenario

Asset Category	\$3.0 million per year (A)		\$5.0 million per year (B)		Replacement Year
	Assets Replaced	Total Expenditure	Assets Replaced	Total Expenditure	
Water Mains	1	\$13,715	7	\$283,240	1
Lift Stations	78	\$2,956,800	128	\$4,712,300.00	
Total	**79**	**\$2,970,515**	**135**	**\$4,995,540**	
Water Mains	6	\$269,525	8	\$552,583	2
Lift Stations	67	\$2,698,500	91	\$4,234,200.00	

Table 35: Continued

Asset Category	$3.0 million per year (A)		$5.0 million per year (B)		Replacement Year
	Assets Replaced	Total Expenditure	Assets Replaced	Total Expenditure	
Total	**73**	**$2,968,025**	**99**	**$4,786,783**	
Water Mains	8	$552,583	10	$1,019,480	**3**
Lift Stations	66	$2,455,200	133	$4,178,300.00	
Total	**74**	**$3,007,783**	**143**	**$5,197,780**	
Water Mains	16	$1,261,294	27	$2,053,531	**4**
Lift Stations	26	$1,701,700	78	$2,725,400.00	
Total	**42**	**$2,962,994**	**105**	**$4,778,931**	
Water Mains	14	$815,873	11	$473,147	**5**
Lift Stations	77	$2,213,500	139	$4,705,800.00	
Total	**91**	**$3,029,373**	**150**	**$5,178,947**	
Water Mains	7	$995,844	93	$3,417,411	**6**
Lift Stations	66	$1,959,200	30	$1,359,400.00	
Total	**73**	**$2,955,044**	**123**	**$4,776,811**	
Water Mains	56	$2,258,522	63	$3,344,764	**7**
Lift Stations	12	$763,900	45	$1,831,800.00	
Total	**68**	**$3,022,422**	**108**	**$5,196,564**	
Water Mains	19	$689,182	151	$4,700,790	**8**
Lift Stations	109	$2,259,200	0	$0	
Total	**128**	**$2,948,382**	**151**	**$4,700,790**	
Water Mains	45	$1,720,823	129	$4,606,629	**9**
Lift Stations	21	$1,321,000	25	$691,800.00	
Total	**66**	**$3,041,823**	**154**	**$5,298,429**	
Water Mains	50	$2,828,257	88	$4,671,581	**10**
Lift Stations	2	$77,000	0	$0	
Total	**52**	**$2,905,257**	**88**	**$4,671,581**	
Overall	**7461**	**$29,811,618**	**1256**	**$49,582,156**	

It can be seen that the number of water mains prioritized to be replaced increases gradually over time in both scenarios. Furthermore, we can also see that the number of water mains decreases with the increase in the number of lift stations and vice-versa. There could be several reasons associated with it, which are discussed as follows:

i. The water mains primarily consist of AC and PVC pipes whose expected useful life is 70 years (Chrysotile Institute) and 100 years (Sustainable Solutions Corp., 2017), respectively. On the other hand, the expected useful life of the assets in the lift stations in the City of Sugar Land ranges from 10 to 30 years. As a result, the probability of failure of the assets in the lift stations is comparatively higher than the assets in the water mains. The higher probability of failure directly correlates to the higher yearly BCP number. Since the designed framework prioritizes the assets based on their yearly BCP number, the majority of the assets in the lift station are replaced earlier than the assets in the water mains. The box plots below show that the average yearly BCP of the replaced assets in the water mains and the lift stations. We can see that the average value of yearly BCP is quite similar in both cases; however, referring back to the values in table 35, more assets in the lift stations are replaced compared to the water mains. From this, it can be understood that there are a higher number of assets scheduled to be replaced in the lift stations in the initial years compared to the assets in the water mains.

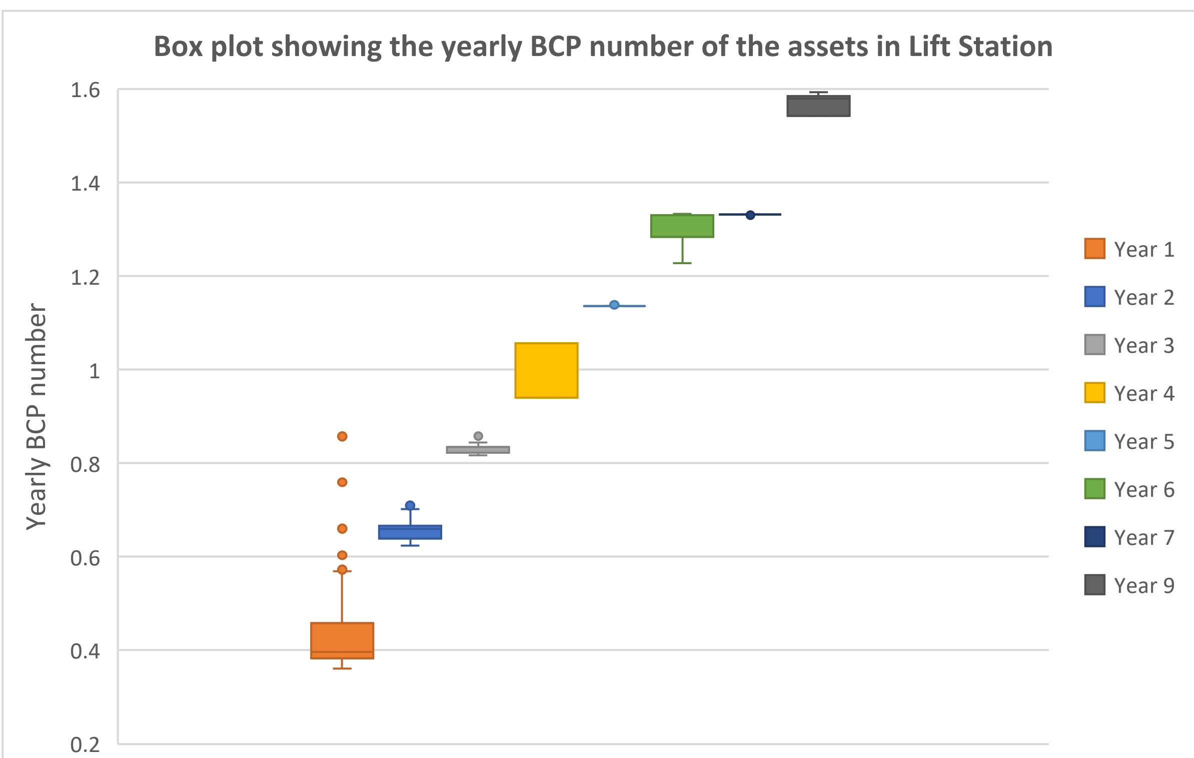


Figure 24: Box Plot showing the yearly BCP number of the assets in the Lift Station

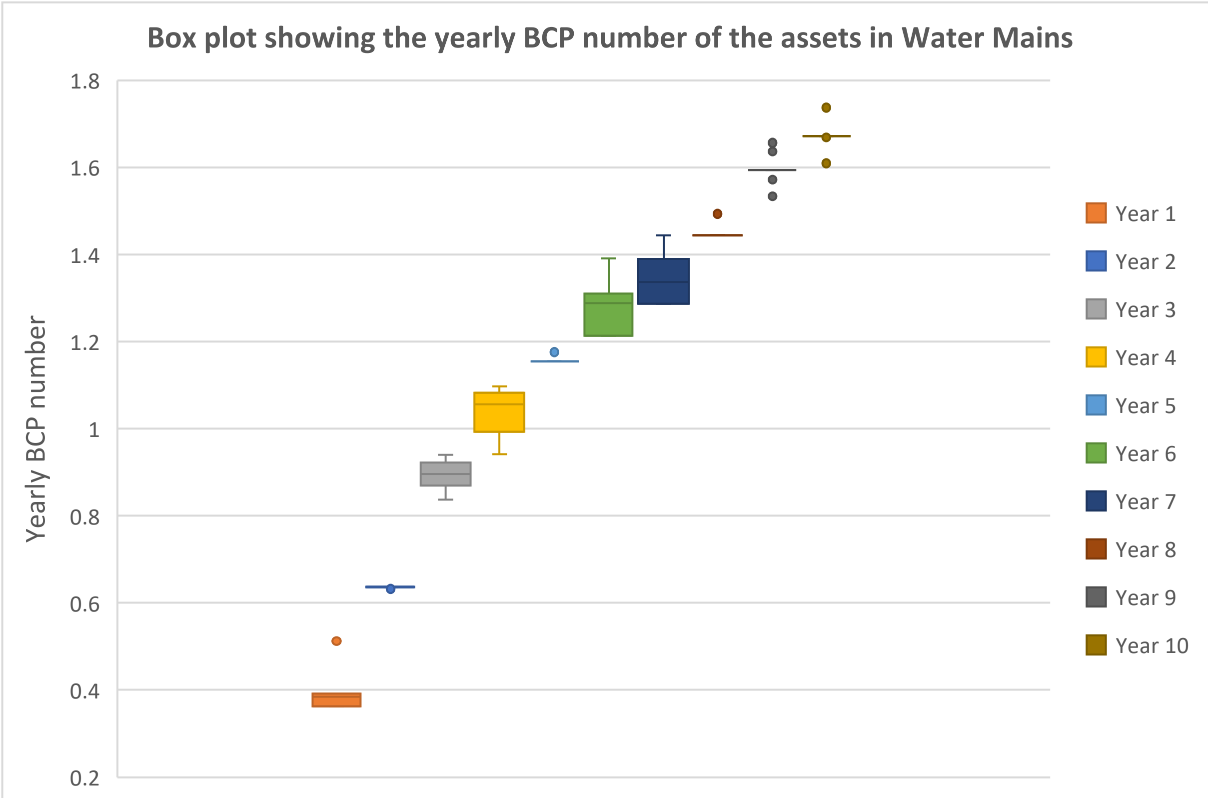


Figure 25: Box Plot showing the yearly BCP of the assets in the Water Mains

ii. The limitation in the funding can be another reason for prioritizing the assets in the lift station over water mains during the initial years. The unit cost of replacement of the assets in the water mains varies from \$60 to \$357 without the casing and \$242 to \$1,200 with the casing (see Appendix). On the other hand, the unit cost of replacement of the assets in the lift station varies from \$1,000 to \$188,000 (see Appendix). The unit costs for water mains might look less than the lift station; however, the total cost of replacement of the water mains is significantly higher than the lift stations because of its length. For example, let us assume that a SCADA panel from the lift station with the replacement costs \$25,000 per unit and a 1000 ft. 6 in. AC pipe from the water mains with the replacement cost of \$60,000 has the same BCP. Given the limitation of the funding, the SCADA panel is selected for the replacement whereas, the AC pipe is postponed for the next year. The table below shows the average replacement cost of the assets in the water mains and the lift stations using the yearly funding scenario of $5.0 million for 10 years.

Table 36: Average replacement cost of the prioritized assets in the Water Mains

Asset Type	Average Diameter	Average Length (ft.)	Average Cost	Total Length (mi.)	Total Cost
Water Mains	6	287.702	$30,726.17	0.327	$184,357.00
Water Mains	8	279.753	$41,281.77	1.907	$1,446,725.00
Water Mains	10	108.74	$22,870.34	2.265	$2,515,737.00
Water Mains	12	223.530	$48,221.46	18.416	$20,976,337.00
Total		**899.976**		**22.916**	**$25,123,156.00**

Table 37: Average replacement cost of the prioritized assets in the Lift Station

Asset Type	Total Count	Average Cost	Total Cost
Controls	99	$70,686.87	$6,998,000.00
Generator ATS	3	$84,666.67	$254,000.00
Grounds	87	$33,655.17	$2,928,000.00
Odor Control	2	$188,000.00	$376,000.00
Pipes	96	$7,995.83	$767,600.00
Portable Bypass Pump	1	$89,000.00	$89,000.00
SCADA	35	$25,000.00	$875,000.00
Stationary Bypass Pump	30	$109,266.67	$3,278,000.00
Sub	181	$32,584.53	$5,897,800.00
Sub Grinder	5	$17,480.00	$87,400.00
Valves	96	$19,283.33	$1,851,200.00
Wet Well	34	$31,088.24	$1,057,000.00
Total	**669**	**$708,707.3068**	**$24,459,000**

From the tables above, we can see that a majority of the 12 in. diameter pipes in the water mains were prioritized for the replacement. The unit cost per feet of 12in. diameter pipe is $119 without the casing and $480 with the casing. Considering the average length of the 12in. diameter pipe to be 215ft. and replacement cost to be $119 per ft., the total cost of replacement of a section of pipe is $25,585 which is greater than the unit replacement cost of the 56% of the assets in the lift stations.

6.2. Analysis of the results in terms of the risk matrices

The risk matrix below provides the visual demonstration of the risk in the water mains by rating them in the categories of likelihood and consequence. The risks are divided into very high, medium, fair, and low categories, and the categories are represented using the red, orange, yellow, and green colors, respectively. The table below shows the comparison of the results of the risk matrix in the water mains using the two funding scenarios. From the table, we can see that, at present, 0.51 and 9.63 miles of pipes in the water mains are at the very high and medium risk category, respectively. Doing nothing for the next 10 years will increase the numbers approximately by fifteen times in very high and seven times in the medium-risk category, making it 8.12 miles and 62.79 miles, respectively. A failure of these assets will result in significant damage to the economy, service, and reputation. However, using a yearly preventive maintenance budget of $3.0 million for 10 years will bring the numbers down to 2.02 miles at very high risk and 59.81 miles at a medium risk category. Increasing the yearly preventive maintenance budget to $5.0 million for 10 years will further decrease the assets at very high risk to 1.86 miles and medium risk to 48.55 miles. In other words, the assets at a very high-risk category will decrease by approximately 75% using the $3.0 million and 77% using the $5.0 million yearly budget for 10 years. Similarly, the assets at a moderate risk category will decrease by approximately 5% and 23% by using the $3.0 million and $5.0 million yearly budget, respectively.

Table 38: Comparison of the results of Water Mains Risk Matrix using multiple scenarios

Water Mains								
Current Scenario			Do Nothing		$3.0 Million per year		$5.0 Million per year	
Risk	Pipe Miles	Total	Pipe Miles	Total	Pipe Miles	Total	Pipe Miles	Total
1	328.03	438.29	126.79	351.77	126.79	355.33	126.79	367.16
2	110.26		224.98		228.60		240.37	
3	125.32	201.73	33.28	227.47	36.24	232.95	36.05	232.78
4	27.66		75.96		78.24		77.87	
5	9.11		103.12		103.18		103.38	
6	39.64		15.11		15.29		15.48	
8	3.67	9.63	10.67	62.79	11.26	59.81	11.77	48.55
9	2.94		1.30		1.30		1.30	
10	0.03		49.26		45.69		33.92	
12	2.99		1.56		1.56		1.56	
15	0.31	0.51	4.72	8.12	1.60	2.02	1.39	1.86
16	0.18		0.13		0.13		0.29	
20	0.02		3.18		0.29		0.00	
25	0.00		0.09		0.00		0.00	
Total	**650.16**	**650.16**	**650.16**	**650.16**	**650.16**	**650.16**	**650.16**	**650.16**

The table below shows the comparison of the results of the risk matrix in the lift stations using the two funding scenarios. From the table, we can see that, at present, 235 and 470 assets in the lift stations are at the very high and medium risk category, respectively. Doing nothing for the next 10 years, the assets at a very high-risk category will increase significantly to 762 which is approximately four times. Similar to that of the water mains, a failure of these assets will also result in significant damage to the economy, service, and reputation. However, using a yearly preventive maintenance budget of $3.0 million for 10 years will bring the numbers down to 243 at very high risk and 438 at a medium risk category. Increasing the yearly preventive maintenance budget to $5.0 million for 10 years will further decrease the number of assets to 112 and 424 at a very high and medium risk category. In other words, the assets at a very high-risk category will decrease by approximately 68% using the $3.0 million and 85% using the $5.0

million yearly budget for 10 years. On contrary, the assets at a moderate risk category will increase by approximately 30% and 25% by using the $3.0 million and $5.0 million yearly budget, respectively. One of the reasons for the increase in the number of the assets in the moderate risk category can be linked to the estimated useful life of the lift stations' assets replaced in the initial years. Assets such as odor controls, portable bypass pumps, and SCADA have a EUL of 10 years; thus, when these get replaced in the early year, the assets will still be prone to failure in the later years. Therefore, despite their replacement in the first couple of years, these assets will continue to have a higher failure probability in later years, resulting in an increase in the number of assets in the moderate risk category.

Table 39: Comparison of the results of Lift Stations Risk Matrix using multiple scenarios

Lift Stations								
Current Scenario			Do Nothing		$3.0 Million per year		$5.0 Million per year	
Risk	**Assets**	**Total**	**Assets**	**Total**	**Assets**	**Total**	**Assets**	**Total**
1	0	8	0	0	0	0	0	0
2	8		0		0		0	
3	17	413	0	26	178	445	194	590
4	120		5		110		128	
5	16		21		35		35	
6	260		0		122		233	
8	103	470	43	338	109	438	109	424
9	152		12		36		36	
10	48		192		197		189	
12	167		91		96		90	
15	144	235	537	762	218	243	96	112
16	43		29		9		0	
20	47		179		16		16	
25	1		17		0		0	
Total	**1126**	**1126**	**1126**	**1126**	**1126**	**1126**	**1126**	**1126**

From the results, we can observe that the overall risk matrix of the water mains does not change notably compared to the lift station. The reason behind this is that out of approximately 34,000 assets in the water mains the model prioritizes replacing roughly around 600, i.e., 1.78%. On the other hand, the model prioritizes replacing around 60% of the assets in the lift station, which significantly changes the risk matrix. However, if we consider the number of assets at very high risk only, we can see a significant reduction in both the water mains and the lift stations.

6.3. Analysis of the results in terms of the network level expected annual number of failures in the linear assets

The network-level failure curve provides information regarding the expected annual number of failures at the network. The expected annual number of failures is the cumulative sum of the annual number of failures at each section. It is very important to calculate the expected annual number of failures because it provides us with the answer to the question of what network-level

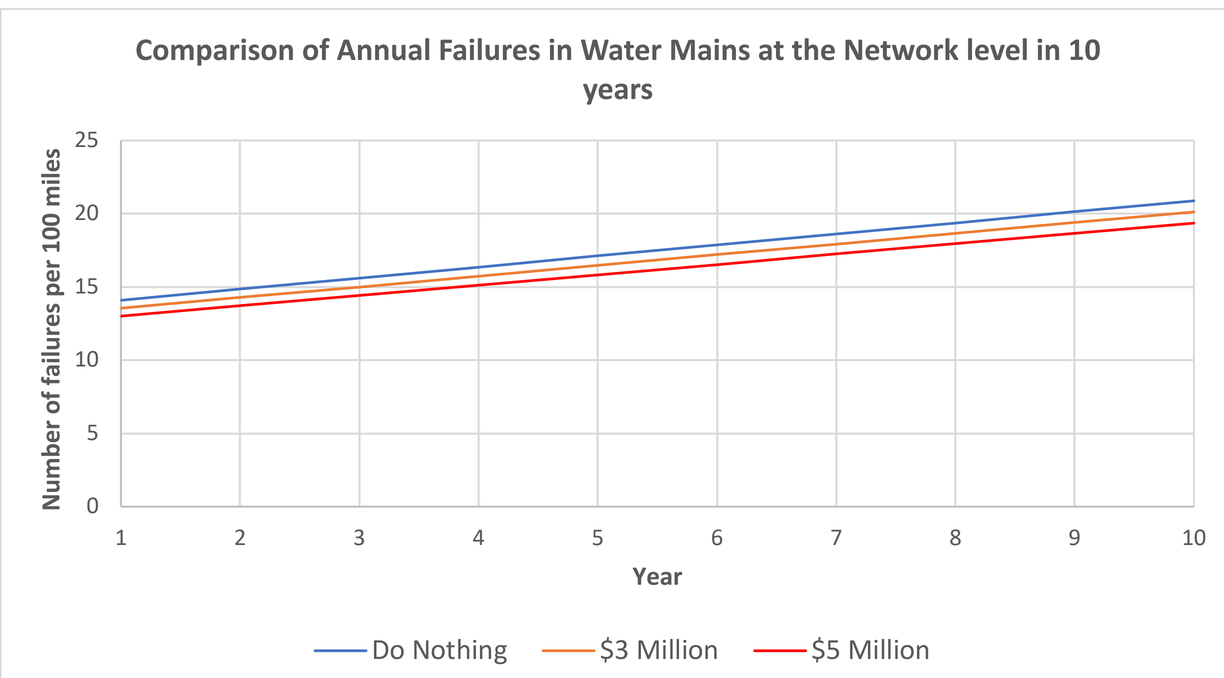


Figure 26: Comparison of expected annual number of failures in Water Mains at the network level

performance can be achieved at what cost? Furthermore, it also helps the decision-makers to define the threshold performance level and allocate the budget accordingly.

The figure above shows the comparison of the expected annual number of failures in the water mains network using the two funding scenarios for 10 years. From the figure, we can observe that the expected annual number of failures in the water mains network is 20.88 failures per 100 miles in 10 years when no preventive maintenance actions are performed. However, using a yearly funding scenario of $3.0 million and $5.0 million would decrease the number to 20.12 and 19.36 failures per 100 miles over 10 years, respectively. The decrease in the expected annual number of failures is not significant because of the following reasons:

i) Since less than 5% of the pipe miles are replaced in both scenarios, the change in the number of failures is not very significant. The number of failures will drastically decrease if the number of pipe miles increases.

ii) A limitation in the funding results in the few sections being prioritized for the replacement, ultimately leading to a small change in the expected annual number of failures. The table below provides an overview of the expected annual failures with the funding scenario.

Table 40: Comparison of expected annual number of failures per 100 miles with multiple funding scenarios

Yearly Budget	Expected Annual Number of Failures per 100 miles	Miles Replaced	Total Miles	% Sections Replaced
$3.0 Million	20.12	11.03	650.16	1.70%
$5.0 Million	19.36	22.92	650.16	3.53%
$6.2 Million	18.57	31.4	650.16	4.83%

It can be observed from the table above that the expected annual number of failures in the water mains network decreases with the increase in the yearly budget. The increase in the budget results in an increase in the miles of pipe being replaced, which significantly decreases the probability of failure.

6.4. Analysis of the results in terms of the network level average reliability in the point assets

The network-level average reliability curve provides information regarding the average reliability of the system at the network level. The network-level average reliability is the average yearly reliability of each asset. Similar to the annual number of failures, the average network level reliability helps the decision-makers to define the threshold performance level and allocate the budget accordingly. The figure below shows the comparison of the yearly average reliability of network using the two funding scenarios for 10 years.

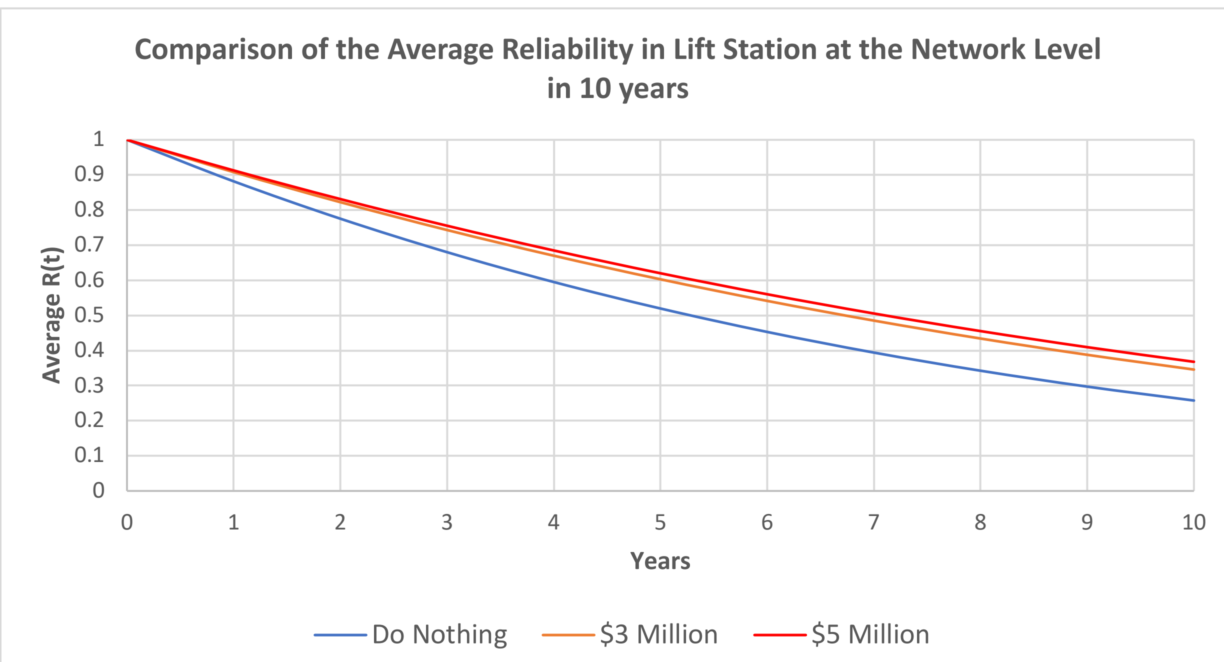


Figure 27: Comparison of average reliability in Lift Station at the network level

From the figure, we can observe that the network level average reliability of the assets in the lift station is 0.25 in 10 years when no preventive maintenance actions are performed. However, using a yearly funding scenario of \$3.0 million and \$5.0 million would increase the average reliability to 0.35 and 0.37 in 10 years, respectively. The increase in the network level average reliability is not significant between the two scenarios because: firstly, only an additional 140 assets get replaced with the \$5.0 million budget scenario compared to the \$3.0 million scenarios. Secondly, most of the assets prioritized for the replacement in the lift stations with expected useful life between 10 to 15 years is subjected to have a higher probability of failure in the later years when replaced early. For example, the probability of failure in the assets such as SCADA, Bypass Pumps, Odor Control, Grounds, and Valves when replaced in initial years is more than 50% in the later years, resulting in a decrease in the network level reliability. Furthermore, the majority of the assets in the lift station prioritized for early replacement belong to the categories mentioned above.

Overall, from the results, it can be observed that the objectives of the decrease in the number of failures, increase in the average reliability, and decrease in the number of assets in the high-risk category in the risk matrix can be achieved by an increase in the annual funding.

7. SUMMARY AND CONCLUSIONS

The goal of this research is to develop a decision-making framework for allocating the budget for the integrated asset management system. The decision-making framework for an integrated asset management system lies in the foundation of economics and engineering principles to maintain the condition of the assets and plan their maintenance. This research project provides a methodology for the management of the multiple facilities in a city using risk-based multi-criteria maintenance and rehabilitation resource allocation.

The first chapter discusses the topic of infrastructure management in general. It discusses the different types of assets in a facility and the challenges in managing them. The challenges primarily include but are not limited to the deteriorating and aging assets, budget constraints, changing customer demands, and socio-economic-environmental considerations. These infrastructures provide services, accommodations, and foster social communication and economic development of a city. It is, therefore, crucial to maintain them despite the challenges. It provides insights into the involvement of the public and private sectors in the business of asset management and highlights the primary reasons for the poor condition of infrastructures by citing it to lack of effective strategic planning, unavailability of budgets, and deficiency in the failure prediction models. The chapter ends by introducing the motivation of this research to develop a model that can combine multiple assets with unique traits into a single domain and effectively plan the MR&R strategies for the city.

The second chapter discusses the background of infrastructure management. It starts by summarizing the deteriorating condition of infrastructures in the United States from the late '80s to the present and discusses the budget deficiency with the required funding to maintain the infrastructures in adequate condition. The chapter discusses a typical infrastructure life cycle can be divided into two stages: construction and maintenance and highlights the importance of the efficient framework for the maintenance stage. The framework should connect the asset database with analytical, engineering, and economic methods to make a rational, objective-centric, and cost-effective decision. Furthermore, the chapter reviews the existing practices of infrastructure management into two categories: ad-hoc and strategic. The ad-hoc or conventional approach involves the MR&R of the assets when need. This approach, however, is limited as a temporary focus on an issue may result in a contrary impact on other operations of other components in a system. The strategic asset management practices, on the other hand, include the use of concepts such as system dynamics, multi-criteria decision analysis, analytical-hierarchical process, decision support system, statistical and mathematical modeling, and risk-based approaches. However, there are multiple hurdles associated with using strategic asset management which includes:

i. The requirement multitude of data such as installation year, utility maps, material type, thickness, diameter, construction details, local policies, and so forth, which may not necessarily be stored and organized by a single owner/entity. Even if available, they usually are disintegrated, inconsistent, and in incompatible formats.
ii. The interdependency problem among the assets, as the maintenance of one infrastructure, may likely to have an impact on the condition of other infrastructures, causing a stream of problems.
iii. The selection of a specific method that could forecast the performance of the infrastructure over time, predict the consequences of a decision on the infrastructure system, and suggest the appropriate measures for it.

The third chapter introduces the term risk along with its terminologies and standard risk management practices in various industries. It further discusses the difference between risk and uncertainty and their assessment in infrastructure management. The uncertainties are mainly induced due to an error in data collection methods or associated with the existing data or historical data, the assumptions in forecasting techniques that deal with the events happening in the future, and residual error resulting from the discrepancy between the model projected and the observed values. The assessment methods include qualitative and quantitative analysis such as i) knowledge-based or expert-based techniques, ii) sensitivity assessment, and iii) probabilistic models. Moreover, the chapter discusses the importance of risk management and the risk management framework in infrastructure management. The chapter introduces the concept of using system reliability and stochastic process for managing the risks of infrastructures and planning their preventive maintenance.

The fourth chapter presents the methodology and framework intending to provide a solution for the cross-asset management problem typically faced by the city councils. The chapter deals with using a risk-based reliability-centric asset management approach to combine the different single asset management strategies into a cross-asset management model. The model works on a basic principle that the risk associated with an asset's failure is the function of the direct and indirect cost of replacement. While the direct cost is the cost per unit of replacement, the indirect cost is the additional cost related to the failure, which cannot be easily quantified in terms of the monetary units. The indirect costs include but may not be limited to the failure to deliver and maintain the required LOS, damage to the reputation, environmental damage, litigations, increase in the backlogs resulting in exceeding budgets, and so forth. The model works by estimating the failure probabilities and the associated consequence of the failure to derive the indirect cost connected with the asset's failure. The indirect costs associated with the failure assets allow the decision-maker to visualize the trade-off between the assets in monetary units. The assets are divided into two categories to predict the failure probabilities: linear assets and point assets. Linear assets are the assets with fixed start and end co-ordinates measured in linear units. In this project, the failure of linear assets is modeled by deriving a relationship between the rate of change of failure (intensity function) from the stochastic process with the failure density function from the reliability process. The relationship works by dividing the linear assets into homogenous sections where the expected number of failures in the sections are independent and follow a binomial expectation. The reason for using this relationship is because the stochastic process provides a good estimate of the network-level failure; nevertheless, it does provide the expected failures in the individual sections when accessing the component level analysis.

On the other hand, point assets are the size and location-specific assets which do not require segmentation for the treatment prioritization. Unlike linear, the condition function for the point assets is only dependent on its type, i.e., the failure in the pipes is dependent not only on its type but also on its length, whereas a specific category of pumps is expected to have a similar nature of the failure. Point assets in this project are modeled using a-2 parameter Weibull distribution where the parameters are the function of the expected life and coefficient of variation of the assets. The failure probabilities in the assets are estimated using a conditional reliability function, which, in turn, is calculated using the effective age of the asset. Effective age is the behavioral age of the asset calculated to generalize their failure patterns. The effective age of an asset is the function of its likelihood of failure, i.e., a two-year-old pump with a higher likelihood of failure is assumed to behave like a ten or twelve-year-old pump, depending on its condition function. The failure probability is then estimated considering that the asset has survived the effective age. The estimated failure probabilities in linear and point assets are combined with the COF and the cost of replacement to determine the yearly BCP number to prioritize the cross-asset maintenance. The BCP number is the benefit that the city gets from replacing a particular asset at a specified year compared to other assets. The chapter further discusses the various clustering approaches to optimize the resource and develop the annual maintenance program. The fifth chapter is the case study where the designed IAMS model was applied to the existing asset database at the City of Sugar Land, TX. The City of Sugar Land has nine different infrastructure facilities: Water, Wastewater, Mobility, Drainage & Stormwater Management, Facilities, Fleets, Parks & Recreation, Aviation, and Information Technology. However, in this project, the methodology was applied only to the water mains and lift station database. The calculations are performed using the queries designed in Microsoft Access, and the results are visualized using the interface in Microsoft Power Bi.

The sixth chapter discusses the results obtained by applying the developed framework in the asset database of the City of Sugar Land. The results of the model are interpreted in terms of:

iv. A decrease in the network level break rate or the number of failures in linear assets.

v. Increase in the average reliability of the network in point assets.

vi. A decrease in the number of assets in a very high- and high-risk category in both linear and point assets.

It was found that objectives of decrease in the network level number of failures, increase in the network level average reliability, and decrease in the number of assets in the high-risk category in the risk matrix can be achieved by an increase in the annual funding. However, an absolute zero risk cannot be achieved unless all the assets are replaced in the same year and analyzed in the following year.

Since the model is designed using SQL, there are still some limitations to the model. Firstly, the queries used in the design of the model are very specific to the data types, fields, and table names. Therefore, even a slight change to the data structure can yield different or no results at all. Secondly, the model considers the replacement of an asset or a component as the best preventive maintenance strategy. Despite the replacement of the assets, we still consider it to be preventive maintenance because it is similar to the analogy of replacing an oil filter in a car, which is the replacement for the filter but preventive maintenance to the overall car. Similarly, the replacement of an asset is the replacement for the asset itself, but it is just a preventive maintenance strategy for the overall network. Therefore, future advancement on this project can be considered both rehabilitation as well as replacement as the viable maintenance strategy and for prioritizing the assets.

Overall, the risk based IAMS model emphasizes a balance in budget allocation and distribution between the facilities by comparing the yearly BCP number among the assets. The higher budget is allocated to those assets which provides maximum benefit to the city. It further allows the decision-makers to compare the risks and benefits of the replacement of the assets from one facility with another.

REFERENCES

Ahmed, E., T., Hegazy. (2012) "Building asset management with deficiency tracking and integrated life cycle optimization." *Structure and Infrastructure Engineering*, 8 (8) pp. 729-738

Al-Kasasbeha, M., Osama, A., Hexu, L. (2020) "An integrated decision support system for building asset management based on WBS." *Journal of Building Engineering*, 32, 101959.

American Society of Civil Engineers (ASCE) (2017). "2017 Infrastructure report card." Accessed: November 9, 2020, from https://www.infrastructurereportcard.org/wp-content/uploads/2016/10/2017-Infrastructure-Report-Card.pdf

American Society of Civil Engineers (ASCE) (2005). "Report card for America's infrastructure." Accessed: September 23, 2020, from www.asce.org/reportcard/

Barry, K., Telford, T., & Laurenson, B. (2001). "How do you manage a vast road network without leaving your desk?" *Perth International Public Works Conference*, Perth, Western Australia.

Beheshti, M. and Sveinung, S. (2018) "Sustainability assessment in strategic management of wastewater transport system: a case study in Trondheim, Norway." *Urban Water Journal*, 15(1), pp. 1-8

Berdica, K. (2002). "An introduction to road vulnerability: what has been done, is done and should be done." *Transport Policy*, 9(2), 117–127.

Black, M., Brint, A. T., and Brailsford, J. R. (2005). "A semi-Markov approach for modelling asset deterioration." *Journal of the Operational Research Society*, 56(11), 1241–1249.

Butt, A. A., Shahin, M. Y., Carpenter, S. H., and Carnahan, J. V. (1994). "Application of Markov process to pavement management systems at network level." *3rd International Conference on Managing Pavements*, National Research Council, Transportation Research Board, Washington, DC, pp. 59–172.

Byrne, R. (2001). "Best practice management networked infrastructure assets." CPA National Congress Conference, Brisbane, Australia.

Cambridge Systems, Inc.; Parsons Brinckerhoff; Quade & Douglas, Inc.; Ray Jorgenson Associates Inc.; Thompson, P. D. (2002). "Transportation Asset Management Guide." *NCHRP Report*, 20–24, Washington D.C.

Chilamkurthy, K. (2020). “Understanding Point Processes.” Medium, Towards Data Science, Accessed: February 13, 2020, from https://towardsdatascience.com/understanding-point-processes-6e3d2f6c5480&gt

Comprehensive Business Improvement Solution (CBIS). (2016). “Project Risk Management.” Assessed: November 30, 2020, from https://www.cbisco.com.au/2014/06/20/project-risk-management/

Crisp, J. and David, B. (2005) “System dynamics modelling: application to electricity transmission network asset management,” *Australian Journal of Electrical and Electronics Engineering*, 2(3), pp. 263-271

Damnjanovic, I., and Reinschmidt, K. F. (2020). “Chapter 1: Introduction to Uncertainty and Risk.” *Data analytics for engineering and construction project risk management*, Springer, Cham, Switzerland.

Damnjanovic, I., and Reinschmidt, K. F. (2020). “Chapter 2: Project Risk Management Fundamentals.” Data analytics for engineering and construction project risk management, Springer, Cham, Switzerland.

De Groot, K., and Thurik, R. (2018). “Disentangling Risk and Uncertainty: When Risk-Taking Measures Are Not About Risk.” *Frontiers in Psychology,* 9, pp. 21- 94

de-Almeida, A. T., Cristiano, A. V. C., Marcelo, H. A., Rodrigo, J. P. F., Adiel, T. F., Thalles, V. G. (2015) “Multi-criteria and Multi-objective Models for Risk, Reliability and Maintenance Decision Analysis”, *International Series in Operations Research & Management Science*, 231

DNV. (2009). "Integrity Management of Submarine Pipeline Systems." *Rep. No. DNVRP-F116*, Det Norske Veritas, Norway.

DNV. (2010). "Risk Assessment of Pipeline Protection." *Rep. No. DNV-RP-F107*, Det
Duncan, W. R. (2013). “A Guide to Project Management Body of Knowledge (PMBOK)”, PMI Standards Committee.

Federal Highway Administration (FWHA). (1999). “Asset management primer.” U.S. Department of Transportation, Office of Asset Management, Washington, D.C.

Fuchs-Hanusch, D., Gangl, G., Kornberger, B., Kölbl, J., Hofrichter, J., and Kainz, H. (2008). “PiRem – Pipe Rehabilitation Management Developing A Decision Support System for Rehabilitation Planning of Water Mains.” *Water Practice and Technology*, 3(1).

Gharaibeh, N. G., and Darter, M. I. (2003). “Probabilistic analysis of highway pavement life for Illinois.” *Transportation Research Record*, 1823, pp. 111–120.

Gustafson, J. M., and Clancy, D. V. (1999). “Modeling the occurrence of breaks in cast iron water mains using methods of survival analysis”. Proceedings of the AWWA Annual Conference.

Hadzilacos, T., Kalles, D., Preston, N., Melbourne, P., Camarinopoulos, L., Eimermacher, M., Kallidromitis, V., Frondistou-Yannas, S., and Saegrov, S. (2000). “UtilNets: a water mains rehabilitation decision-support system.” *Computers, Environment and Urban System*s, 24(3), pp. 215–232.

Han, J., Kamber, M., and Tung, A. (2001). “Spatial Clustering Methods in Data Mining: A survey.” *Geographic Data Mining and Knowledge Discovery, Research Monographs in* GIS, Research Monographs in GIS, Taylor and Francis

Herz, R. K. (1996). “Aging processes and rehabilitation needs of drinking water distribution networks.” *Journal of Water Supply: Research and Technology*, 45(5), pp. 221-231.

Huang, I.B., Keisler, J., and Linkov, I. (2011). “Multi-criteria decision analysis in environmental sciences: Ten years of applications and trends.” *Science of the Total Environment*, 409(19), pp. 3578–3594.

Humphreys, E. (2010). Information security risk management: Handbook for ISO/IEC 27001. London: British Standards Institution (BSI).

International Organization for Standardization. (2009). “Risk management - principles and guidelines.” ISO 31000:2009, Geneva.

Jamal, H. (2017). “Reasons for Infrastructure Deterioration.” Accessed: September 23, 2020, from https://www.aboutcivil.org/why-infrastructure-deteriorates

Jeffrey, L. A. (1985). “Predicting urban water distribution maintenance strategy: A case study of New Haven, Connecticut.” Massachusetts Institute of Technology.

Kabir, G. (2012). “Multiple Criteria Inventory Classification Under Fuzzy Environment.” *International Journal of Fuzzy System Applications (IJFSA)*, 2(4), pp. 76-92.

Kiker, G.A., Bridges, T.S., Varghese, A., Seager, P.T., Linkov, I. (2005). “Application of multicriteria decision analysis in environmental decision making.” *Integrated Environmental Assessment and Management*, 1(2), pp. 95–108.

Kulkarni, R., Golabi, K., and Chuang, J. (1986). "Analytical techniques for selection of repair or-replace options for cast-iron gas piping systems - Phase I". Technical report, Chicago.

Lai, E., Lundie, S., Ashbolt, N.J. (2008). "Review of multi-criteria decision aid for integrated sustainability assessment of urban water systems." *Urban Water Journal*, 5(4), pp. 315–327.

Lind, E. A., Farr, J. V., Kays, J. L. (1997). "Resource allocation for army installation management." *Journal of Infrastructure Systems*, 3, pp. 177–182.

Liu, L., and Gharaibeh, N. G. (2014). "A Bayesian model for predicting the performance of pavements treated with thin HMA overlays." *Transportation Research Record*, 2431(1), pp. 33–41.

Marlow, D., Scott, G., and Bradley, L. (2015). "An expert system for assessing the technical and economic risk of pipe rehabilitation options." *Expert Systems with Applications*, 42(22), pp. 8658-8668

Martins, A., Leitão, J. P., and Amado, C. (2013). "Comparative Study of Three Stochastic Models for Prediction of Pipe Failures in Water Supply Systems." *Journal of Infrastructure Systems*, 19(4), pp. 442–450

Melchers, R.E. (2009). "Structural reliability: analysis and prediction", Wiley, New York

Menendez, J. R., and Gharaibeh, N. G. (2017). "Incorporating Risk and Uncertainty into Infrastructure Asset Management Plans for Pavement Networks." *Journal of Infrastructure Systems*, 23(4)

Mishalani, R. G., and Madanat, S. M. (2002). "Computation of infrastructure transition probabilities using stochastic duration models." *Journal of Infrastructure Systems*, 8(4), pp. 139–148

Nordgård, D. E. and Maria, D. C. (2011). "Integrating risk analysis and multi-criteria decision support under uncertainty in electricity distribution system asset management", *Reliability Engineering & System Safety*, 96(6), 663-670

O.M. Salem, Richard, A. M., Abhijeet, S. D., Tejas P. A. (2013) "Multi-criteria decision-making system for selecting an effective plan for bridge rehabilitation", *Structure and Infrastructure Engineering*, 9(8), pp. 806-816

Ouyang, M. (2014). "Review on modeling and simulation of interdependent critical infrastructure systems." *Reliability Engineering & System* Safety, 121, pp. 43-60

Piyatrapoomi, N., Kumar, A., and Setunge, S. (2004). "Framework for Investment Decision-Making Under Risk and Uncertainty for Infrastructure Asset Management." *Research in Transportation Economics*, 8, 199–214.

Rackwitz. R. (2001). "Reliability analysis-a review and some perspectives." *Structural Safety,* 23(4)*,* 365–395

Rashedi, R. and Tarek, H. (2016) "Strategic policy analysis for infrastructure rehabilitation using system dynamics." *Structure and Infrastructure Engineering*, 12(6) pp. 667-681

Recchia, V. (2002). "Risk communication and public perception of technological hazard." *FEEM Working Paper*. (1)

Recchia, V. (2002). "Risk communication and public perception of technological hazard." *FEEM Working Paper*. (2)

Remenyte-Prescott, R. and Andrews, J. (2013). "Review of Infrastructure Asset Management Methods for Networked Systems." *Advances in Risk and Reliability Technology Symposium*, U.K

S. Syachrani, Jeong, H.S., Chung, C.S. (2011). "Dynamic deterioration models for sewer pipe network." *Journal of Pipeline Systems Engineering and Practice*, 2(4), pp. 123-131

Sadiq, R., and Tesfamariam, S. (2009). "Multi-criteria decision-making (MCDM) using intuitionistic fuzzy analytic hierarchy process (IF-AHP)." *Stochastic Environmental Research and Risk Assessment*, 23(1), pp. 75–91

Seyedolshohadaie, S. R. (2011). "Modeling Risks in Infrastructure Asset Management." Doctoral dissertation, Texas A&M University, College Station, TX.

Shamir, U., and Howard, C. (1979). "Analytic approach to scheduling pipe replacement." *Journal of American Water Works Association*,71(5), pp. 248-258

Shao, L. and Chun, Q. L. (2007). "Reliability Based Asset Management Strategy for Concrete Infrastructure", *International Journal of Materials & Structural Reliability*, 5(1), 13–28

Syed, Z. and Yuri, L. (2020). "Multi-criteria decision-making considering risk and uncertainty in physical asset management", *Journal of Loss Prevention in the Process Industries*, 65

Ter Berg, C. J. A., George, L., Martine, V. D. B., Matthijs, T. S., and Rogier, W. (2019). "Expert judgement-based maintenance decision support method for structures with a long service-life." *Structure and Infrastructure Engineering,* 15, pp. 492 – 503

Tesfamariam, S., and Sadiq, R. (2006). “Risk-based environmental decision-making using fuzzy analytic hierarchy process (F-AHP).” *Stochastic Environmental Research and Risk Assessment*, 21(1), pp. 35–50

Thompson, P. D. and Johnson, M. B. (2005). Markovian bridge deterioration: developing models from historical data. Structure and Infrastructure Engineering, 1, pp. 85–91.

Walker, W. E. (2000). “Policy analysis: a systematic approach to supporting policymaking in the public sector.” *Journal of Multi-Criteria Decision Analysis*, 9(1-3), 11–27

Wei, L., Heshan, D., Quratul-ain, M., Kareem, A., Derek, R. M., Barry, C., Vania, D., David, G., David, E., Helen, R., Anthony, G. C. (2020). “A decision support system for urban infrastructure inter-asset management employing domain ontologies and qualitative uncertainty-based reasoning.” *Expert Systems with Applications*, 158

Wijnia, Y. (2011). “Processing Risk in Asset Management”, Doctoral dissertation, Delft University of Technology, Netherlands

APPENDIX A

A.1 Weibull Conditional Reliability for the assets with the EUL 10

Years	R(t)	F(t)	R(t|5)	F(t|5)	R(t|8)	F(t|8)	R(t|10)	F(t|10)	R(t|13)	F(t|13)	R(t|15)	F(t|15)
0	1.0000	0.0000										
1	0.9879	0.0121										
2	0.9579	0.0421										
3	0.9139	0.0861										
4	0.8589	0.1411										
5	0.7959	0.2041	1.0000	0.0000								
6	0.7274	0.2726	0.9140	0.0860								
7	0.6561	0.3439	0.8244	0.1756								
8	0.5843	0.4157	0.7341	0.2659	1.0000	0.0000						
9	0.5138	0.4862	0.6456	0.3544	0.8794	0.1206						
10	0.4463	0.5537	0.5608	0.4392	0.7638	0.2362	1.0000	0.0000				
11	0.3830	0.6170	0.4812	0.5188	0.6555	0.3445	0.8582	0.1418				
12	0.3248	0.6752	0.4081	0.5919	0.5559	0.4441	0.7278	0.2722				
13	0.2723	0.7277	0.3421	0.6579	0.4660	0.5340	0.6101	0.3899	1.0000	0.0000		
14	0.2256	0.7744	0.2835	0.7165	0.3861	0.6139	0.5055	0.4945	0.8286	0.1714		
15	0.1848	0.8152	0.2322	0.7678	0.3163	0.6837	0.4142	0.5858	0.6789	0.3211	1.0000	0.0000
16	0.1497	0.8503	0.1881	0.8119	0.2563	0.7437	0.3355	0.6645	0.5500	0.4500	0.8101	0.1899
17	0.1200	0.8800	0.1507	0.8493	0.2053	0.7947	0.2688	0.7312	0.4406	0.5594	0.6491	0.3509
18	0.0951	0.9049	0.1195	0.8805	0.1627	0.8373	0.2130	0.7870	0.3492	0.6508	0.5144	0.4856
19	0.0745	0.9255	0.0936	0.9064	0.1276	0.8724	0.1670	0.8330	0.2737	0.7263	0.4032	0.5968
20	0.0578	0.9422	0.0726	0.9274	0.0989	0.9011	0.1295	0.8705	0.2123	0.7877	0.3127	0.6873
21	0.0443	0.9557	0.0557	0.9443	0.0759	0.9241	0.0994	0.9006	0.1629	0.8371	0.2399	0.7601
22	0.0337	0.9663	0.0423	0.9577	0.0576	0.9424	0.0754	0.9246	0.1237	0.8763	0.1822	0.8178
23	0.0253	0.9747	0.0318	0.9682	0.0433	0.9567	0.0567	0.9433	0.0929	0.9071	0.1369	0.8631
24	0.0188	0.9812	0.0236	0.9764	0.0322	0.9678	0.0421	0.9579	0.0691	0.9309	0.1018	0.8982
25	0.0138	0.9862	0.0174	0.9826	0.0237	0.9763	0.0310	0.9690	0.0508	0.9492	0.0749	0.9251

26	0.0101	0.9899	0.0127	0.9873	0.0173	0.9827	0.0226	0.9774	0.0370	0.9630	0.0545	0.9455
27	0.0073	0.9927	0.0091	0.9909	0.0124	0.9876	0.0163	0.9837	0.0267	0.9733	0.0393	0.9607
28	0.0052	0.9948	0.0065	0.9935	0.0089	0.9911	0.0116	0.9884	0.0191	0.9809	0.0281	0.9719
29	0.0037	0.9963	0.0046	0.9954	0.0063	0.9937	0.0082	0.9918	0.0135	0.9865	0.0198	0.9802
30	0.0026	0.9974	0.0032	0.9968	0.0044	0.9956	0.0057	0.9943	0.0094	0.9906	0.0139	0.9861
31	0.0018	0.9982	0.0022	0.9978	0.0030	0.9970	0.0040	0.9960	0.0065	0.9935	0.0096	0.9904
32	0.0012	0.9988	0.0015	0.9985	0.0021	0.9979	0.0027	0.9973	0.0045	0.9955	0.0066	0.9934
33	0.0008	0.9992	0.0010	0.9990	0.0014	0.9986	0.0019	0.9981	0.0030	0.9970	0.0045	0.9955
34	0.0006	0.9994	0.0007	0.9993	0.0010	0.9990	0.0012	0.9988	0.0020	0.9980	0.0030	0.9970
35	0.0004	0.9996	0.0005	0.9995	0.0006	0.9994	0.0008	0.9992	0.0014	0.9986	0.0020	0.9980

A.2 Weibull Conditional Reliability for the assets with the EUL 15

Years	R(t)	F(t)	R(t|8)	F(t|8)	R(t|12)	F(t|12)	R(t|15)	F(t|15)	R(t|19)	F(t|19)	R(t|23)	F(t|23)
0	1.0000	0.0000										
1	0.9942	0.0058										
2	0.9796	0.0204										
3	0.9579	0.0421										
4	0.9299	0.0701										
5	0.8966	0.1034										
6	0.8589	0.1411										
7	0.8176	0.1824										
8	0.7735	0.2265	1.0000	0.0000								
9	0.7274	0.2726	0.9404	0.0596								
10	0.6801	0.3199	0.8792	0.1208								
11	0.6321	0.3679	0.8172	0.1828								
12	0.5843	0.4157	0.7553	0.2447	1.0000	0.0000						
13	0.5370	0.4630	0.6943	0.3057	0.9191	0.0809						
14	0.4909	0.5091	0.6346	0.3654	0.8402	0.1598						
15	0.4463	0.5537	0.5769	0.4231	0.7638	0.2362	1.0000	0.0000				
16	0.4036	0.5964	0.5217	0.4783	0.6907	0.3093	0.9043	0.0957				

17	0.3630	0.6370	0.4693	0.5307	0.6213	0.3787	0.8134	0.1866				
18	0.3248	0.6752	0.4199	0.5801	0.5559	0.4441	0.7278	0.2722				
19	0.2891	0.7109	0.3738	0.6262	0.4948	0.5052	0.6479	0.3521	1.0000	0.0000		
20	0.2560	0.7440	0.3310	0.6690	0.4382	0.5618	0.5737	0.4263	0.8856	0.1144		
21	0.2256	0.7744	0.2917	0.7083	0.3861	0.6139	0.5055	0.4945	0.7803	0.2197		
22	0.1978	0.8022	0.2557	0.7443	0.3385	0.6615	0.4432	0.5568	0.6840	0.3160		
23	0.1725	0.8275	0.2230	0.7770	0.2953	0.7047	0.3866	0.6134	0.5967	0.4033	1.0000	0.0000
24	0.1497	0.8503	0.1936	0.8064	0.2563	0.7437	0.3355	0.6645	0.5179	0.4821	0.8680	0.1320
25	0.1293	0.8707	0.1672	0.8328	0.2213	0.7787	0.2898	0.7102	0.4473	0.5527	0.7496	0.2504
26	0.1111	0.8889	0.1437	0.8563	0.1902	0.8098	0.2491	0.7509	0.3844	0.6156	0.6443	0.3557
27	0.0951	0.9049	0.1229	0.8771	0.1627	0.8373	0.2130	0.7870	0.3288	0.6712	0.5511	0.4489
28	0.0809	0.9191	0.1046	0.8954	0.1385	0.8615	0.1813	0.8187	0.2799	0.7201	0.4691	0.5309
29	0.0685	0.9315	0.0886	0.9114	0.1173	0.8827	0.1536	0.8464	0.2371	0.7629	0.3973	0.6027
30	0.0578	0.9422	0.0747	0.9253	0.0989	0.9011	0.1295	0.8705	0.1999	0.8001	0.3350	0.6650
31	0.0485	0.9515	0.0627	0.9373	0.0830	0.9170	0.1087	0.8913	0.1677	0.8323	0.2811	0.7189
32	0.0405	0.9595	0.0524	0.9476	0.0693	0.9307	0.0907	0.9093	0.1401	0.8599	0.2348	0.7652
33	0.0337	0.9663	0.0435	0.9565	0.0576	0.9424	0.0754	0.9246	0.1164	0.8836	0.1951	0.8049
34	0.0279	0.9721	0.0360	0.9640	0.0477	0.9523	0.0624	0.9376	0.0963	0.9037	0.1615	0.8385
35	0.0229	0.9771	0.0297	0.9703	0.0393	0.9607	0.0514	0.9486	0.0793	0.9207	0.1330	0.8670
36	0.0188	0.9812	0.0243	0.9757	0.0322	0.9678	0.0421	0.9579	0.0650	0.9350	0.1090	0.8910
37	0.0153	0.9847	0.0198	0.9802	0.0263	0.9737	0.0344	0.9656	0.0531	0.9469	0.0890	0.9110
38	0.0125	0.9875	0.0161	0.9839	0.0213	0.9787	0.0279	0.9721	0.0431	0.9569	0.0723	0.9277
39	0.0101	0.9899	0.0130	0.9870	0.0173	0.9827	0.0226	0.9774	0.0349	0.9651	0.0584	0.9416
40	0.0081	0.9919	0.0105	0.9895	0.0139	0.9861	0.0182	0.9818	0.0281	0.9719	0.0470	0.9530
41	0.0065	0.9935	0.0084	0.9916	0.0111	0.9889	0.0146	0.9854	0.0225	0.9775	0.0377	0.9623
42	0.0052	0.9948	0.0067	0.9933	0.0089	0.9911	0.0116	0.9884	0.0179	0.9821	0.0301	0.9699
43	0.0041	0.9959	0.0053	0.9947	0.0071	0.9929	0.0092	0.9908	0.0143	0.9857	0.0239	0.9761
44	0.0033	0.9967	0.0042	0.9958	0.0056	0.9944	0.0073	0.9927	0.0113	0.9887	0.0189	0.9811
45	0.0026	0.9974	0.0033	0.9967	0.0044	0.9956	0.0057	0.9943	0.0089	0.9911	0.0149	0.9851
46	0.0020	0.9980	0.0026	0.9974	0.0034	0.9966	0.0045	0.9955	0.0070	0.9930	0.0117	0.9883

47	0.0016	0.9984	0.0020	0.9980	0.0027	0.9973	0.0035	0.9965	0.0054	0.9946	0.0091	0.9909
48	0.0012	0.9988	0.0016	0.9984	0.0021	0.9979	0.0027	0.9973	0.0042	0.9958	0.0071	0.9929
49	0.0009	0.9991	0.0012	0.9988	0.0016	0.9984	0.0021	0.9979	0.0033	0.9967	0.0055	0.9945
50	0.0007	0.9993	0.0009	0.9991	0.0012	0.9988	0.0016	0.9984	0.0025	0.9975	0.0042	0.9958

A.3 Weibull Conditional Reliability for the assets with the EUL 20

Years	R(t)	F(t)	R(t|10)	F(t|10)	R(t|15)	F(t|15)	R(t|20)	F(t|20)	R(t|25)	F(t|25)	R(t|30)	F(t|30)
0	1.0000	0.0000										
1	0.9966	0.0034										
2	0.9879	0.0121										
3	0.9748	0.0252										
4	0.9579	0.0421										
5	0.9374	0.0626										
6	0.9139	0.0861										
7	0.8876	0.1124										
8	0.8589	0.1411										
9	0.8282	0.1718										
10	0.7959	0.2041	1.0000	0.0000								
11	0.7622	0.2378	0.9576	0.0424								
12	0.7274	0.2726	0.9140	0.0860								
13	0.6920	0.3080	0.8695	0.1305								
14	0.6561	0.3439	0.8244	0.1756								
15	0.6201	0.3799	0.7792	0.2208	1.0000	0.0000						
16	0.5843	0.4157	0.7341	0.2659	0.9422	0.0578						
17	0.5487	0.4513	0.6895	0.3105	0.8849	0.1151						
18	0.5138	0.4862	0.6456	0.3544	0.8285	0.1715						
19	0.4796	0.5204	0.6026	0.3974	0.7733	0.2267						
20	0.4463	0.5537	0.5607	0.4393	0.7196	0.2804	1.0000	0.0000				
21	0.4140	0.5860	0.5202	0.4798	0.6677	0.3323	0.9278	0.0722				

22	0.3830	0.6170	0.4812	0.5188	0.6176	0.3824	0.8582	0.1418				
23	0.3532	0.6468	0.4438	0.5562	0.5696	0.4304	0.7915	0.2085				
24	0.3248	0.6752	0.4081	0.5919	0.5238	0.4762	0.7278	0.2722				
25	0.2978	0.7022	0.3742	0.6258	0.4802	0.5198	0.6673	0.3327	1.0000	0.0000		
26	0.2723	0.7277	0.3421	0.6579	0.4390	0.5610	0.6101	0.3899	0.9142	0.0858		
27	0.2482	0.7518	0.3119	0.6881	0.4002	0.5998	0.5561	0.4439	0.8334	0.1666		
28	0.2256	0.7744	0.2835	0.7165	0.3638	0.6362	0.5055	0.4945	0.7576	0.2424		
29	0.2045	0.7955	0.2569	0.7431	0.3297	0.6703	0.4582	0.5418	0.6867	0.3133		
30	0.1848	0.8152	0.2322	0.7678	0.2980	0.7020	0.4142	0.5858	0.6206	0.3794	1.0000	0.0000
31	0.1666	0.8334	0.2093	0.7907	0.2686	0.7314	0.3733	0.6267	0.5594	0.4406	0.9013	0.0987
32	0.1497	0.8503	0.1881	0.8119	0.2415	0.7585	0.3355	0.6645	0.5028	0.4972	0.8101	0.1899
33	0.1342	0.8658	0.1686	0.8314	0.2164	0.7836	0.3007	0.6993	0.4507	0.5493	0.7261	0.2739
34	0.1200	0.8800	0.1507	0.8493	0.1935	0.8065	0.2688	0.7312	0.4028	0.5972	0.6491	0.3509
35	0.1069	0.8931	0.1344	0.8656	0.1724	0.8276	0.2396	0.7604	0.3591	0.6409	0.5786	0.4214
36	0.0951	0.9049	0.1195	0.8805	0.1533	0.8467	0.2130	0.7870	0.3192	0.6808	0.5144	0.4856
37	0.0843	0.9157	0.1059	0.8941	0.1359	0.8641	0.1889	0.8111	0.2830	0.7170	0.4560	0.5440
38	0.0745	0.9255	0.0936	0.9064	0.1202	0.8798	0.1670	0.8330	0.2502	0.7498	0.4032	0.5968
39	0.0657	0.9343	0.0826	0.9174	0.1060	0.8940	0.1473	0.8527	0.2207	0.7793	0.3555	0.6445
40	0.0578	0.9422	0.0726	0.9274	0.0932	0.9068	0.1295	0.8705	0.1941	0.8059	0.3127	0.6873
41	0.0507	0.9493	0.0637	0.9363	0.0817	0.9183	0.1136	0.8864	0.1702	0.8298	0.2743	0.7257
42	0.0443	0.9557	0.0557	0.9443	0.0715	0.9285	0.0994	0.9006	0.1489	0.8511	0.2399	0.7601
43	0.0387	0.9613	0.0486	0.9514	0.0624	0.9376	0.0867	0.9133	0.1299	0.8701	0.2093	0.7907
44	0.0337	0.9663	0.0423	0.9577	0.0543	0.9457	0.0754	0.9246	0.1130	0.8870	0.1821	0.8179
45	0.0292	0.9708	0.0367	0.9633	0.0471	0.9529	0.0655	0.9345	0.0981	0.9019	0.1581	0.8419
46	0.0253	0.9747	0.0318	0.9682	0.0408	0.9592	0.0567	0.9433	0.0849	0.9151	0.1368	0.8632
47	0.0218	0.9782	0.0274	0.9726	0.0352	0.9648	0.0489	0.9511	0.0733	0.9267	0.1182	0.8818
48	0.0188	0.9812	0.0236	0.9764	0.0303	0.9697	0.0421	0.9579	0.0632	0.9368	0.1018	0.8982
49	0.0162	0.9838	0.0203	0.9797	0.0260	0.9740	0.0362	0.9638	0.0542	0.9458	0.0874	0.9126
50	0.0138	0.9862	0.0174	0.9826	0.0223	0.9777	0.0310	0.9690	0.0465	0.9535	0.0749	0.9251

A.4 Weibull Conditional Reliability for the assets with the EUL 25

Years	R(t)	F(t)	R(t|13)	F(t|13)	R(t|19)	F(t|19)	R(t|25)	F(t|25)	R(t|32)	F(t|32)	R(t|38)	F(t|38)
0	1.0000	0.0000										
1	0.9977	0.0023										
2	0.9919	0.0081										
3	0.9832	0.0168										
4	0.9717	0.0283										
5	0.9579	0.0421										
6	0.9418	0.0582										
7	0.9236	0.0764										
8	0.9037	0.0963										
9	0.8820	0.1180										
10	0.8589	0.1411										
11	0.8345	0.1655										
12	0.8090	0.1910										
13	0.7825	0.2175	1.0000	0.0000								
14	0.7553	0.2447	0.9652	0.0348								
15	0.7274	0.2726	0.9296	0.0704								
16	0.6991	0.3009	0.8934	0.1066								
17	0.6705	0.3295	0.8569	0.1431								
18	0.6417	0.3583	0.8201	0.1799								
19	0.6129	0.3871	0.7833	0.2167	1.0000	0.0000						
20	0.5843	0.4157	0.7466	0.2534	0.9532	0.0468						
21	0.5558	0.4442	0.7103	0.2897	0.9068	0.0932						
22	0.5277	0.4723	0.6743	0.3257	0.8609	0.1391						
23	0.5000	0.5000	0.6390	0.3610	0.8157	0.1843						
24	0.4728	0.5272	0.6042	0.3958	0.7714	0.2286						
25	0.4463	0.5537	0.5703	0.4297	0.7281	0.2719	1.0000	0.0000				
26	0.4204	0.5796	0.5372	0.4628	0.6859	0.3141	0.9420	0.0580				

27	0.3953	0.6047	0.5051	0.4949	0.6448	0.3552	0.8857	0.1143				
28	0.3709	0.6291	0.4740	0.5260	0.6051	0.3949	0.8311	0.1689				
29	0.3474	0.6526	0.4440	0.5560	0.5668	0.4332	0.7785	0.2215				
30	0.3248	0.6752	0.4151	0.5849	0.5299	0.4701	0.7278	0.2722				
31	0.3031	0.6969	0.3873	0.6127	0.4945	0.5055	0.6791	0.3209				
32	0.2823	0.7177	0.3607	0.6393	0.4605	0.5395	0.6326	0.3674	1.0000	0.0000		
33	0.2624	0.7376	0.3354	0.6646	0.4282	0.5718	0.5881	0.4119	0.9297	0.0703		
34	0.2435	0.7565	0.3112	0.6888	0.3973	0.6027	0.5457	0.4543	0.8627	0.1373		
35	0.2256	0.7744	0.2883	0.7117	0.3680	0.6320	0.5055	0.4945	0.7992	0.2008		
36	0.2086	0.7914	0.2666	0.7334	0.3403	0.6597	0.4674	0.5326	0.7389	0.2611		
37	0.1925	0.8075	0.2460	0.7540	0.3141	0.6859	0.4314	0.5686	0.6820	0.3180		
38	0.1774	0.8226	0.2267	0.7733	0.2894	0.7106	0.3974	0.6026	0.6283	0.3717	1.0000	0.0000
39	0.1631	0.8369	0.2084	0.7916	0.2661	0.7339	0.3655	0.6345	0.5778	0.4222	0.9196	0.0804
40	0.1497	0.8503	0.1913	0.8087	0.2443	0.7557	0.3355	0.6645	0.5304	0.4696	0.8442	0.1558
41	0.1372	0.8628	0.1753	0.8247	0.2238	0.7762	0.3075	0.6925	0.4860	0.5140	0.7736	0.2264
42	0.1255	0.8745	0.1604	0.8396	0.2048	0.7952	0.2812	0.7188	0.4446	0.5554	0.7077	0.2923
43	0.1146	0.8854	0.1465	0.8535	0.1870	0.8130	0.2568	0.7432	0.4060	0.5940	0.6462	0.3538
44	0.1045	0.8955	0.1335	0.8665	0.1704	0.8296	0.2341	0.7659	0.3701	0.6299	0.5890	0.4110
45	0.0951	0.9049	0.1215	0.8785	0.1551	0.8449	0.2130	0.7870	0.3368	0.6632	0.5360	0.4640
46	0.0864	0.9136	0.1104	0.8896	0.1409	0.8591	0.1935	0.8065	0.3059	0.6941	0.4869	0.5131
47	0.0783	0.9217	0.1001	0.8999	0.1277	0.8723	0.1755	0.8245	0.2774	0.7226	0.4415	0.5585
48	0.0709	0.9291	0.0906	0.9094	0.1156	0.8844	0.1588	0.8412	0.2511	0.7489	0.3997	0.6003
49	0.0641	0.9359	0.0819	0.9181	0.1045	0.8955	0.1435	0.8565	0.2269	0.7731	0.3612	0.6388
50	0.0578	0.9422	0.0738	0.9262	0.0943	0.9057	0.1295	0.8705	0.2047	0.7953	0.3258	0.6742

A.5 Cost of Replacement of Pipes with their diameters in the Water Mains

Pipe Description	Min Diameter	Max Diameter	Replace Cost Open Cut / Boring	Replace Cost w/ Casing
6 in	0	6	$60	$242
8 in	6	8	$79	$323
10 in	8	10	$99	$403
12 in	10	12	$119	$480
14 in	12	14	$139	$565
16 in	14	16	$159	$646
18 in	16	18	$179	$727
20 in	18	20	$198	$808
22 in	20	22	$218	$888
24 in	22	24	$238	$969
26 in	24	26	$258	$1,005
28 in	26	28	$278	$1,045
30 in	28	30	$298	$1,080
32 in	30	32	$317	$1,110
36 in	32	36	$357	$1,200

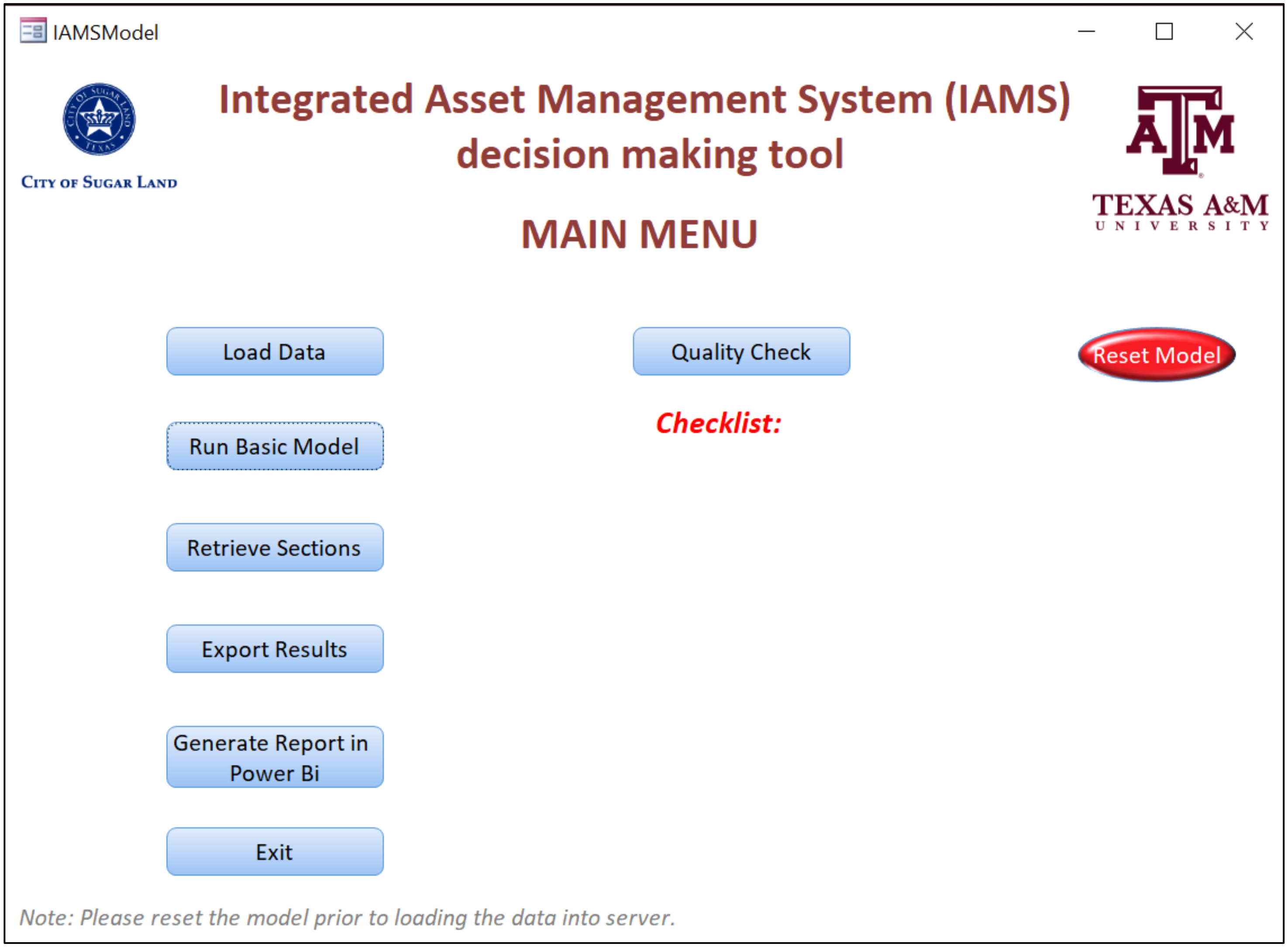
A.6 Cost of Replacement of Assets in the Lift Stations

Asset Type	Facility Size	Replacement Cost	Asset Type	Facility Size	Replacement Cost
Blower	Small	$2,800	Generator ATS	Large	$102,000
Controls	Large duplex	$78,000	Generator ATS	Small duplex	$50,000
Controls	Small duplex	$63,000	Grounds	Large duplex	$36,000
Controls	Medium	$69,000	Grounds	Large	$54,000
Controls	Small	$1,000	Grounds	Medium	$28,000
Controls	Large	$93,000	Grounds	Small duplex	$23,000
Generator ATS	Medium	$69,000	Grounds	Small	$1,000
Generator ATS	Large duplex	$71,000	Odor Control	Large	$188,000

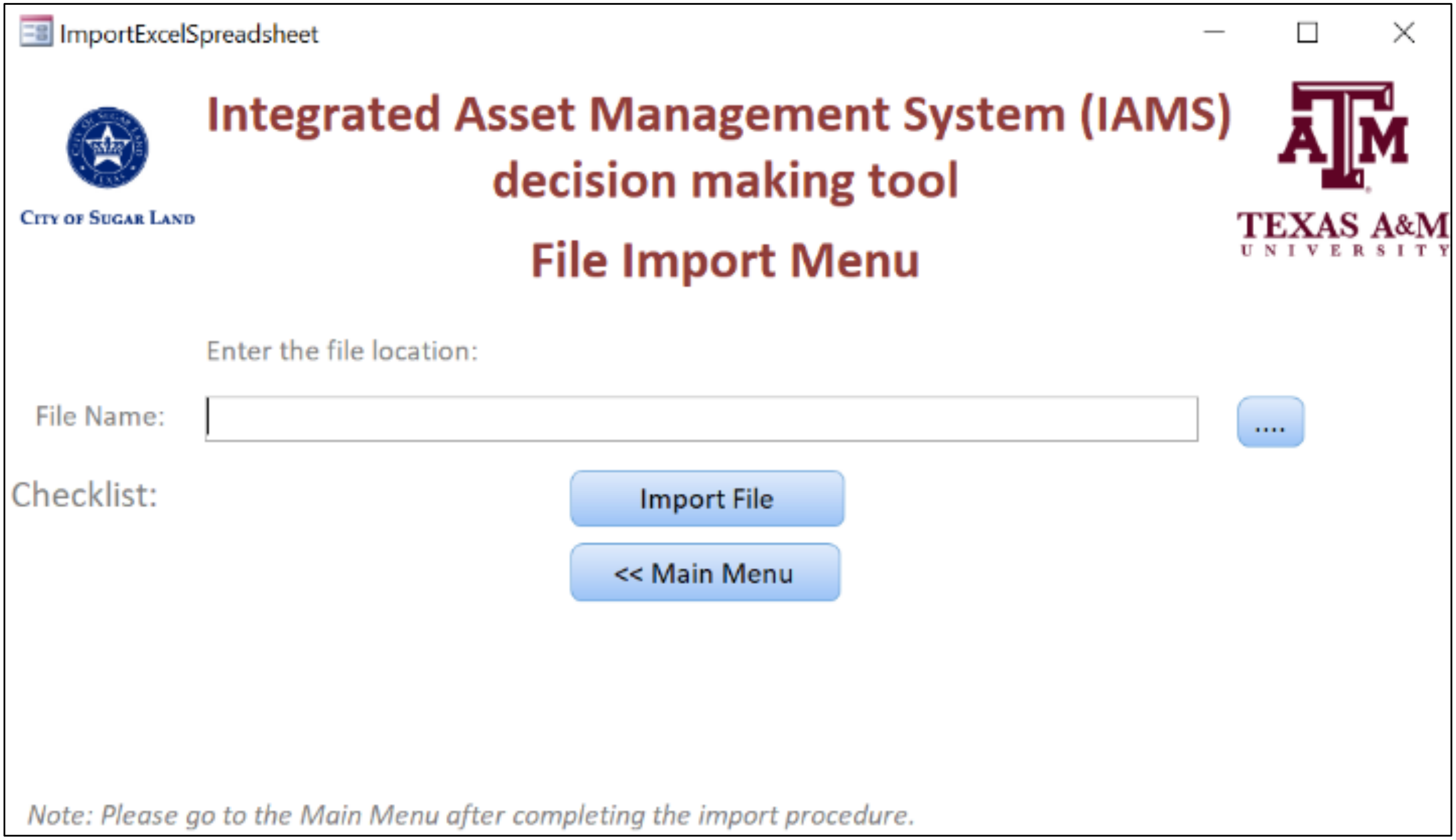
Asset Type	Facility Size	Replacement Cost	Asset Type	Facility Size	Replacement Cost
Pipes	Medium	$7,000	Sub	Medium	$21,000
Pipes	Large	$17,000	Sub	Small	$2,800
Pipes	Large duplex	$8,000	Sub	Small duplex	$17,000
Pipes	Small duplex	$7,000	Sub	Large duplex	$39,000
Pipes	Small	$400	Sub	Large	$58,000
Portable Bypass Pump	Small duplex	$89,000	Sub Grinder	Large	$58,000
SCADA	Small duplex	$25,000	Sub Grinder	Medium	$21,000
SCADA	Small	$25,000	Sub Grinder	Small duplex	$17,000
SCADA	Large duplex	$25,000	Sub Grinder	Large duplex	$39,000
SCADA	Large	$25,000	Sub Grinder	Small	$2,800
SCADA	Medium	$25,000	Valves	Small	$400
Self-Prime Cent	Small duplex	$17,000	Valves	Small duplex	$14,000
Self-Prime Cent	Medium	$21,000	Valves	Medium	$15,000
Self-Prime Cent	Small	$2,800	Valves	Large duplex	$19,000
Self-Prime Cent	Large duplex	$39,000	Valves	Large	$49,000
Self-Prime Cent	Large	$58,000	Wet Well	Small	$2,700
Stationary Bypass Pump	Small duplex	$89,000	Wet Well	Small duplex	$16,000
Stationary Bypass Pump	Medium	$89,000	Wet Well	Large duplex	$31,000
Stationary Bypass Pump	Large	$132,000	Wet Well	Large	$63,000
Stationary Bypass Pump	Large duplex	$98,000	Wet Well	Medium	$21,000

APPENDIX B

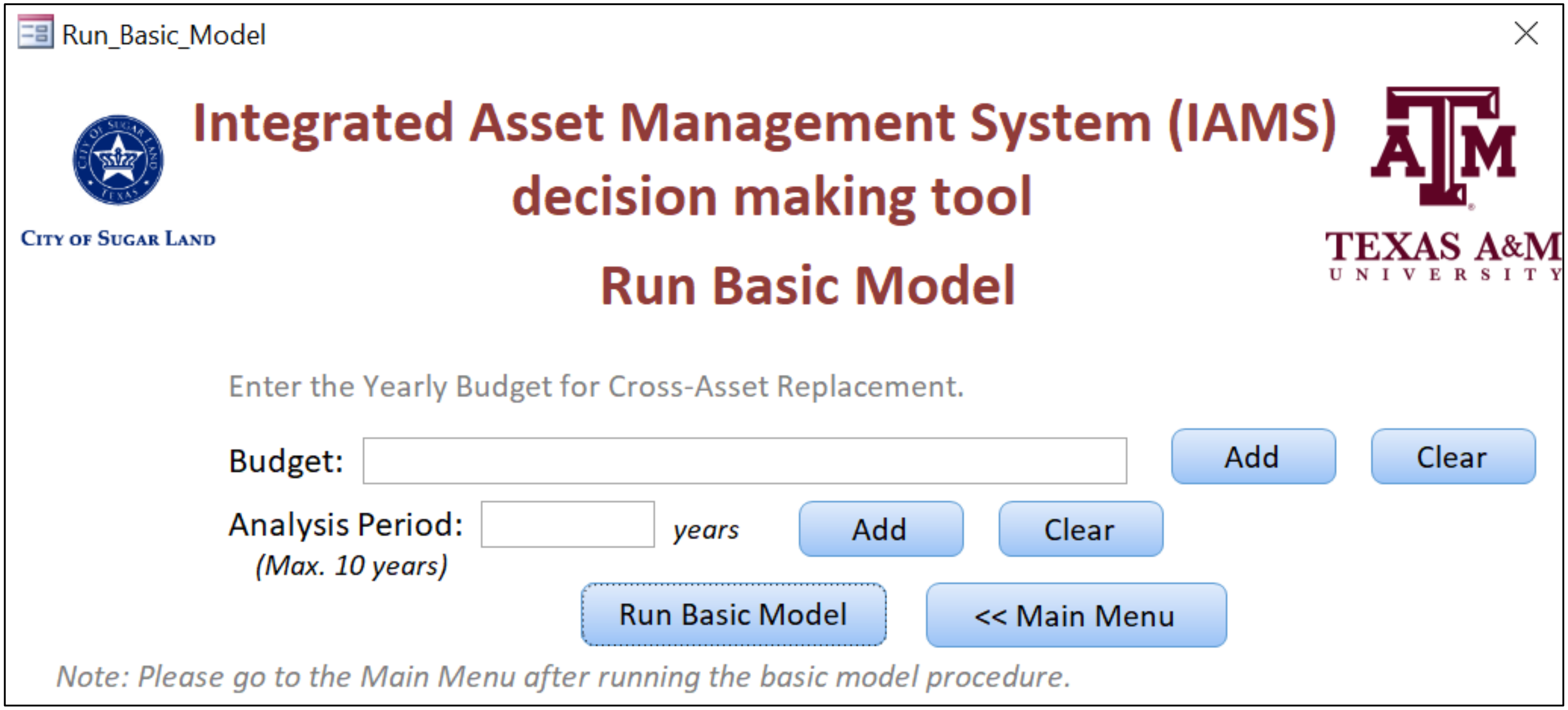
B.1 User Interface of the designed Integrated Asset Management System (IAMS) – Main Menu



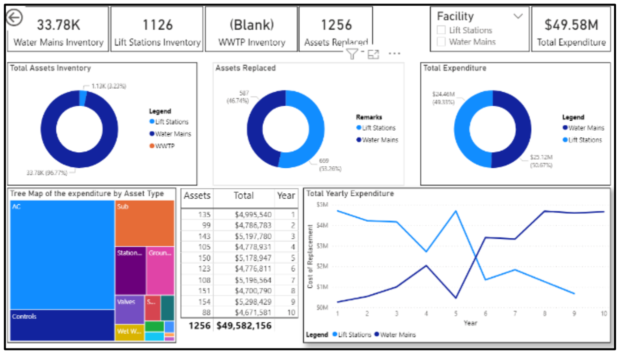
B.2 User Interface of the designed Integrated Asset Management System (IAMS) – File Import Menu



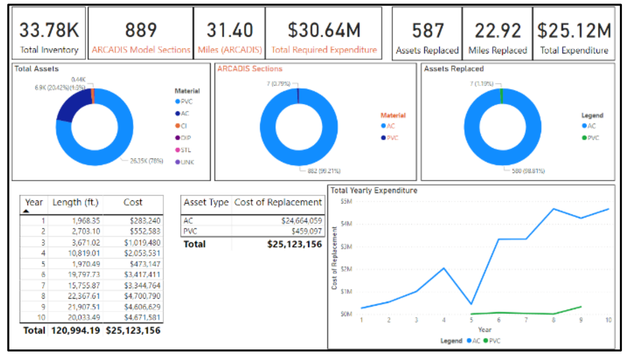
B.3 User Interface of the designed Integrated Asset Management System (IAMS) – Run Basic Model



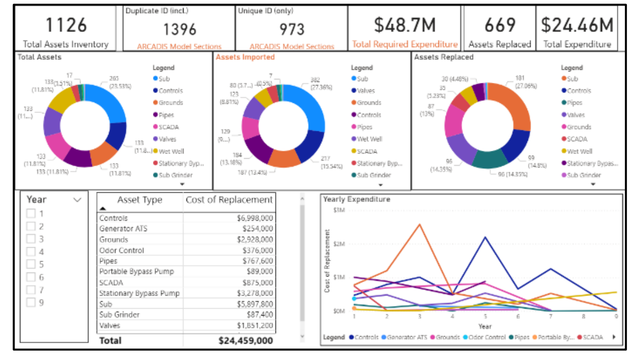
B.4 User Interface of the designed Integrated Asset Management System (IAMS) – Power Bi Visualization Dashboard



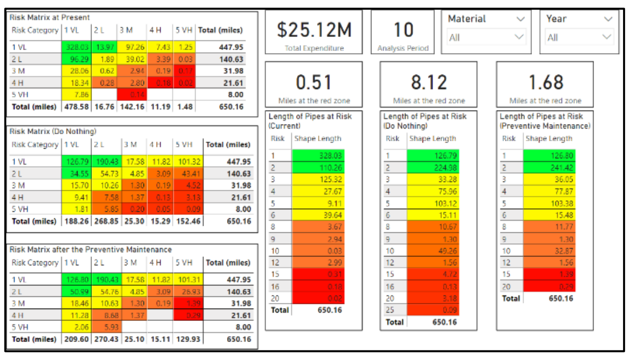
Cross-Asset Dashboard



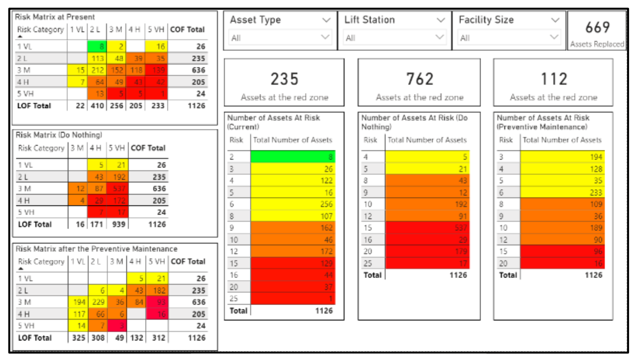
Water Mains Dashboard



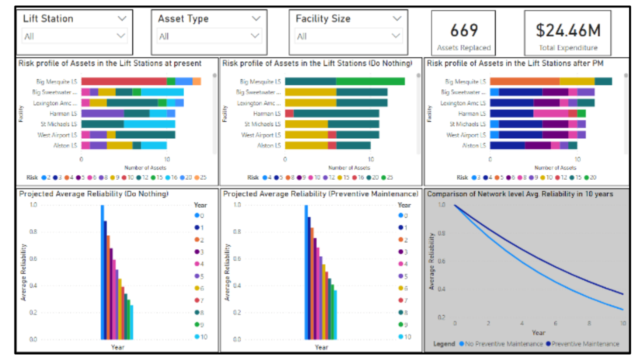
Lift Stations Dashboard



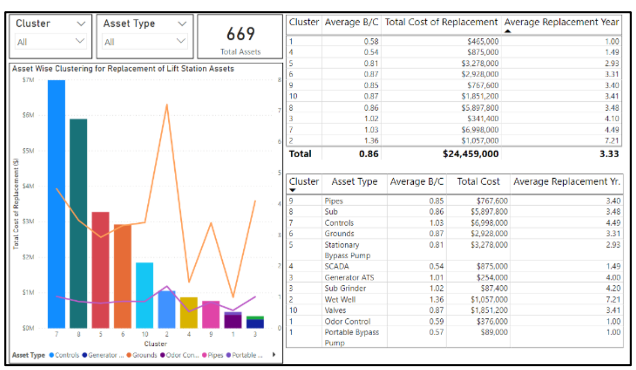
Water Mains Risk Matrix



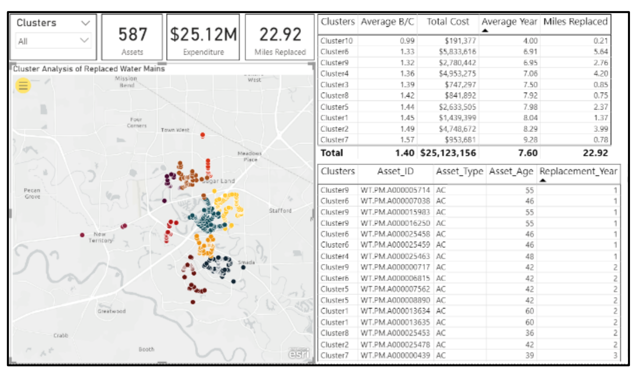
Lift Stations Risk Matrix



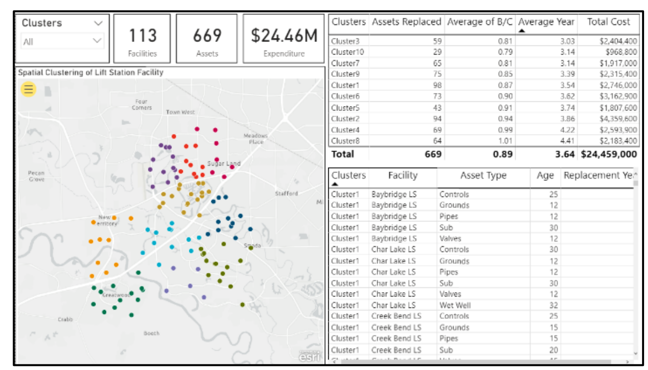
Lift Stations Risk Analysis



Lift Stations Asset-wise clustering



Water Mains Spatial Clustering



Lift Stations Spatial Clustering